
Advanced Modelling, Control and Energy Optimization of Railway Traction Power Supply Systems

By

CHEN XING



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School of Electronic & Electrical Engineering
Faculty of Engineering
UNIVERSITY OF LEEDS

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ABSTRACT

As part of the effort to achieve the Paris agreement climate goals, in June 2019, the UK government passed the legislation and set a stringent target aiming for net zero greenhouse gas (GHG) emissions by 2050, becoming the first major economy to take concrete steps to tackle the issue of climate change. It is gradually acknowledged that greenhouse gas removal (GGR) is an essential measure for the UK to meet its objectives of carbon emission reduction.

As reported, the total emissions of the UK in 2021 reached 447 MtCO_{2e}, where the surface transport sector accounted to 23%, which became the largest source of emissions in the UK. Amongst, personal road transport means emitted more carbon dioxide (CO₂) on average than other land transport modes, therefore shifting towards a higher share of public and mass transit will be essential. Railways are recognised as one of the most energy-efficient modes of transportation for both passengers and freight. However, in the UK, only 38% of the existing railway network has been electrified by year 2021.

In this context, on the one hand, the electrification of the railway sector needs to be further promoted. On the other hand, there are still great potentials to enhance the energy efficiency for the existing electrified AC railway traction power supply system. Meanwhile, with significant penetration of renewable energy and integration of energy storage systems (ESS), it brings great opportunities to achieve railway net-zero, but also more challenges to the design, control, stability and reliability, and energy management of the railway power supply system. The trend moving from traditional railway power supply system to more efficient smart one has become predominant.

The primary objective of this thesis is to explore various techniques that can be used to optimize energy efficiency in AC railway traction power supply systems. This research begins with a comprehensive review of the scope of railway traction power supply system and energy optimization in Chapter 2. Then, targeting at the raised challenges, in Chapter 3, a multi-objective optimization power compensation strategy based on the NSGA-II algorithm has been proposed for the railway co-phase power supply system with renewable

energy integration, to reduce the system operation capacity while addressing the power quality issues. In Chapter 4, continuing to focus on the railway co-phase power supply system with ESS integration, a DQN-based thermal constrained energy management strategy has been proposed to achieve the peak load shaving and constrain the temperature increase for both the power electronics modules and ESS so as to enhance their reliability. In Chapter 5, for the train operation side, a bi-objective robust optimization model for the train speed trajectories has been formulated to minimize both the energy consumption and journey time, in which the robustness against the uncertain train mass is also considered and viewed as a decision maker (DM) preference. A novel multi-objective optimization algorithm namely p-NSGA-II has been proposed to handle the formulated problem, incorporating the original NSGA-II and a proposed preference dominance criterion. The energy optimization for the AC railway traction power supply system is investigated from both railway power supply side and train operation side. This includes the development of advanced optimization algorithms and techniques, the use of regenerative braking power, renewable energy and energy storage systems, and the optimization of train trajectory planning. The research also addresses the challenges associated with complex system modelling of the railway traction power supply system with renewable and ESS integration, system reliability and robustness enhancement, and power quality improvement.

Overall, this research presents a comprehensive framework on the modeling, control and energy optimization to support the development of efficient smart railway traction power supply systems with a transition from the legacy systems, and provides valuable insights into various key issues relating to the construction of sustainable railway transportation systems.

NOMENCLATURE

Chapter 1. Abbreviations

CO ₂	Carbon dioxide
CO ₂ e	Carbon dioxide equivalent
ESS	Energy storage system
GGR	Greenhouse gas removal
GHG	Greenhouse gas
HS1	High Speed 1
HS2	High Speed 2
ORR	Office of Rail and Road
PFC	Power flow controller

Chapter 2. Abbreviations

AC	Alternating current
ACO	Ant colony optimization
ARMG	AC railway microgrid
AT	Auto Transformer
BT	Boost Transformer
DC	Direct current
DER	Distributed energy resource
DL	Deep learning
DP	Dynamic programming
EMU	Electric multiple unit
ERS	Electric railway systems
IFC	Interfacing converter
ILP	Integer linear programming

LP Linear programming
MG Microgrid
MMC Modular multilevel converter
PET Power electronic transformer
PSO Particle swarm optimization
PV Photovoltaic
QP Quadratic programming
RBE Regenerative braking energy
RPC Railway power conditioner
SFC Static frequency converter
SG Smart grid
STATCOM Static synchronous compensator
SVC Static VAR compensator

Chapter 3. Abbreviations

APC Active power compensator
HPQC Hybrid power quality conditioner
NSGA-II Nondominated sorting genetic algorithm-II

Chapter 3. Parameters and Variables

$\tilde{I}_a, \tilde{I}_b, \tilde{I}_c$ Secondary currents
 $\tilde{I}_A, \tilde{I}_B, \tilde{I}_C$ Three-phase voltages
 $\tilde{V}_A, \tilde{V}_B, \tilde{V}_C$ Three-phase voltages
 $\tilde{V}_{ac}, \tilde{V}_{bc}$ Secondary voltages
 $\varphi_a, \varphi_b, \varphi_c$ Phase angles of a, b and c
 φ_L Phase angle of traction load
 I_{ap}, I_{cap}, I_{cbp} Active currents of different ports
 I_{aq}, I_{caq}, I_{cbq} Reactive currents of different ports
 K Compensation factor
 $K_{optimal}$ Optimal power compensation factor
 P_L, Q_L Active and reactive traction load
 P_{RE} Renewable power

Chapter 4. Abbreviations

DNN Deep neural network
DRL Deep reinforcement learning
EMU Electrical multi units
ESS Energy storage system
FRA Fast recursive algorithm
HESS Hybrid energy storage system
IGBT Insulated gate bipolar transistor
MDP Markov decision process
MILP Mixed integer linear programming
MMC Modular multilevel converter
MPC Model predictive control
PFC Power flow controller
SoC State of charge
TPSS Traction power supply system

Chapter 4. Parameters and Variables

C_1, C_2 Battery internal and shell thermal capacity
 $C_{E.T}, C_{E.D}$ Temperature coefficients of switching loss
 C_{ESS} Rated capacity of ESS
 f_{sw} Switching frequency
 $I_{ref}, V_{ref}, T_{ref}$ Reference current, voltage, and temperature
 K_v, K_i Correction coefficient of voltage and current for power loss
 k_1, k_2 Heat conduction coefficients
 P_a, Q_a Active and reactive power from phase a
 $P_{ca}, Q_{ca}, P_{cb}, Q_{cb}$ Active and reactive compensation power of converters A and B
 P_{con}, P_{sw} Conduction loss and switching loss
 P_{ESS} Charging/discharging power of ESS
 S_L, P_L, Q_L, φ_L Apparent power, active power, reactive power and phase angle of traction loads

T_{amb} Ambient temperature
 T_{in}, T_{sh} Battery internal and shell temperature
 T_j, T_h Junction temperature and heat sink temperature

Chapter 5. Abbreviations

ADP Approximate dynamic programming
ATO Automatic train operation
DM Decision maker
GA Genetic algorithm
HS High speed
LS Low speed
MILP Mixed-integer linear programming
MOEA Multi-objective evolutionary algorithm
MOPSO Multi-objective particle swarm optimization
MS Medium speed
NSGA-II Nondominated sorting genetic algorithm-II
PMP Pontryagin's maximum principle
PR Performance robustness
RO Robust optimization
ROI Region of interest
SO Stochastic optimization
SR Scheme robustness

Chapter 5. Parameters and Variables

a Acceleration rate
 α, β, γ Empirical coefficients of basic resistance
 $\overline{M}$ Average train mass
 $\overline{M}_p$ Average passenger mass
 θ Ramp angle
 E Energy consumption
 F Traction/braking force
 F_{max} Maximum traction/braking force

M	Train mass
M_p	Passenger mass
M_v	Empty vehicle mass
P_{max}	Rated motor power
R_1	Basic resistance
r_1	Per unit basic resistance
R_2	Additional resistance
T	Journey time
V	Speed control sequence of whole journey
$v_{i,b}$	Braking speed of subsection i
$v_{i,c}$	Cruising speed of subsection i
$v_{i,e}$	End speed of subsection i
$v_{i,s}$	Start speed of subsection i
V_i	Speed control sequence of subsection i

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DECLARATION

I declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements.

Details of the publications which has been used in this thesis are as following:

- In Chapter 3: Xing C, Li K, Zhang L, Li W. Optimal compensation control of railway co-phase traction power supply integrated with renewable energy based on NSGA-II [J]. IET Renewable Power Generation, 2020, 14(18): 3668-3678.
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- In Chapter 4: Xing C, Li K, Su J. Thermal Constrained Energy Optimization of Railway Co-phase Systems with ESS Integration-An FRA-pruned DQN Approach [J]. IEEE Transactions on Transportation Electrification, 2022.
As the lead author, the candidate contributed to the work including the system modelling, algorithm development, validation as well as paper drafting. Prof. Kang Li checked the equation derivations and results. Jialei Su did the data collection and analysis.
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INTRODUCTION

1.1 Background

The Paris Agreement in 2015 announces to hold the increase in the global warming to a maximum of 2°C above pre-industrial level and even to put further efforts into limiting the temperature increase to 1.5°C [2, 3]. While it has been gradually recognized that traditional methods of addressing climate change are becoming increasingly inadequate in achieving the climate targets [4]. Based on the output of the first round of Nationally Determined Contributions under the Paris Agreement, it has been observed that states' climate commitments are not only inadequate, but also that insufficient progress has been made towards achieving these commitments [4, 5]. Even if decarbonization has been significantly progressed in some areas, it remains very challenging to reduce carbon emissions in specific areas by traditional approaches [4, 6]. Furthermore, the previous carbon emissions have already had irreversible impacts on the climate change, and will continue to accelerate the warming trend that traditional methods will be incapable of mitigating [4].

As part of the effort to achieve the Paris agreement climate goals, in June 2019, the UK government passed the legislation and set a stringent target aiming for net zero

greenhouse gas (GHG) emissions by 2050, becoming the first major economy to take concrete steps to tackle the issue of climate change [3, 4]. It is gradually acknowledged that greenhouse gas removal (GGR) is an essential measure for the UK to meet the objectives of carbon emission reduction [4, 7].

As released in [1], the total emissions of the UK in 2021 reached 447 MtCO₂e, where the surface transport sector accounted to 23%, becoming the largest source of emissions in the UK. As shown in Figure 1.1, personal road transport means emitted more carbon dioxide (CO₂) on average than other land transport modes, therefore shifting towards a higher share of public and mass transit will be essential [1, 8, 9].

Railways are recognised as one of the most energy-efficient modes of transportation for both passengers and freight. However, in the UK, only 38% of the existing railway network has been electrified by year 2021 [10, 11]. According to the Office of Rail and Road (ORR) report released on 25 August 2022, the emissions are 358 g/km CO₂e per electric passenger vehicle and 211 g/km CO₂e per electric freight vehicle [12]. While the diesel trains emit 1400 g/km CO₂e for passenger use and 598 g/km CO₂e for freight use [12]. Over the next few decades, trains that run on diesel-based internal combustion engines will be gradually eliminated. As a result, long-term plans are crucial for achieving the 2050 target of carbon emission reduction. On the one hand, the current global effort to reduce fossil fuel consumption and its associated greenhouse effect is putting more pressure on the rail industry to accelerate the electrification of key routes, which can contribute to decarbonization across the entire rail sector. On the other hand, the rail sector is upgrading its existing infrastructure to increase the power supply capacity and improve the energy efficiency [11].

The railway electrification in the UK can be traced back to more than a century ago. The first electric railway in the UK was Volk's Electric Railway in Brighton, which is opened in 1883, and still in operation today [13]. The City and South London Railway, which is now part of the London Underground Northern line, started the electric services in 1890 using a fourth rail system [13]. In contrast, the Liverpool Overhead Railway was designed to be electric traction from the outset and began operating in 1893 [13].

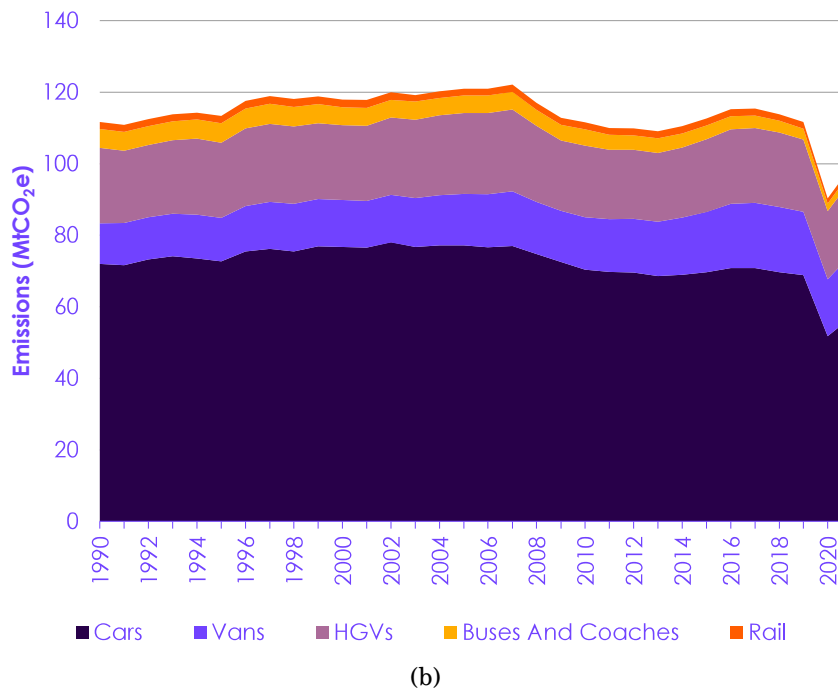
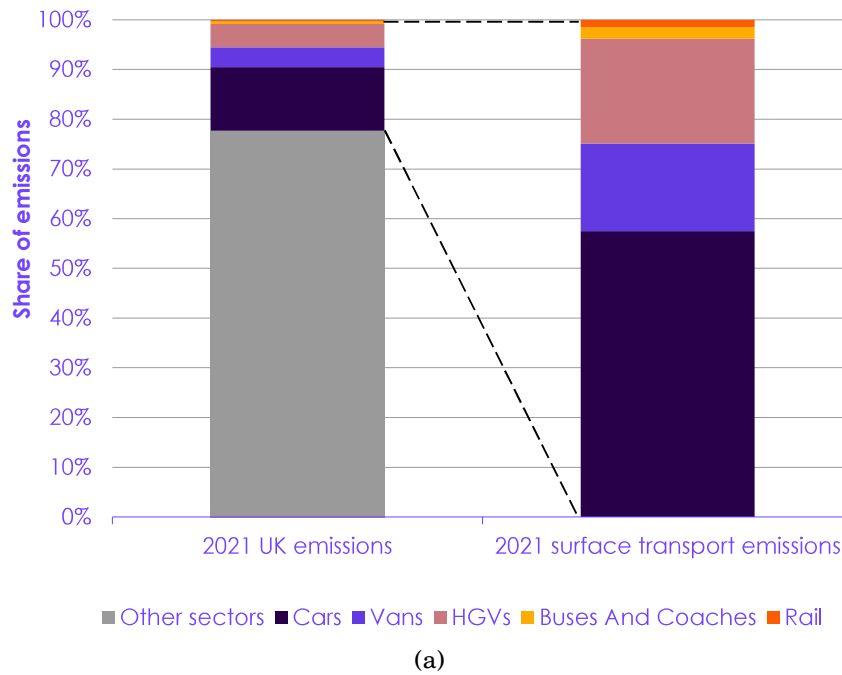


Figure 1.1: Carbon emissions of surface transport by subsector. [1]

Beginning from the early 20th century, the technology advancement of electrified railways continues to surge ahead, as a result of remarkable progress in electrical engineering, mechanical engineering, power electronics, and also automation. Entering the 21st

century, Network Rail initiated a consultation on significant electrification projects in 2009 [13]. These projects had the potential to include the Great Western Main Line and the Midland Main Line [13]. The main benefits of electric trains were their ability to operate at higher speeds, greater reliability, and less track wear compared to diesel trains since, as a general trend, electric trains without the large fuel tank tend to be lighter than diesel trains [13, 14]. In July 2012, the UK government unveiled a new set of electrification schemes totaling £4.2 billion, all of which were to be powered by 25 kV AC [13, 15].

Worldwide, to meet increasing transportation demand, many countries have developed plans for constructing electrified high-speed railway. Britain, known as the inventor of railway transportation, also has set up the scheme to construct the major high-speed railway lines. The High Speed 1 (HS1) line, which is 67 miles long, links London to the Channel Tunnel and facilitates international Eurostar services to France, Belgium, and the Netherlands [16]. Trains on this line travel at speeds of up to 186 mph (300 km/h). The construction of another major high-speed rail line, High Speed 2 (HS2), has been underway since 2019 [16]. This line will connect London with major cities in the North and the Midlands, reducing journey times to Scotland, and will operate at speeds of up to 224 mph (360 km/h) [16, 17].

Even though massive rail electrification efforts have been made worldwide, as reported in [12], the emissions from diesel consumption still dominate the railway emissions. Thus, there still remains a great potential to decarbonize the entire rail sector by continuing to progress railway electrification.

1.2 Challenges

In the context of the railway decarbonization, the introduction of renewable energy and energy storage system (ESS) is naturally promoted, and there is also a need to improve the energy efficiency of railway traction power supply. Given the inherent characteristics of railway traction power supply system and the integration of renewable and ESS, there

are a set of emerging challenges as listed below to be addressed.

Power Quality Issues - The power quality issues caused by the interaction between the traction power supply system and the main utility grid have become a major concern. On the one hand, the conversion of traction power to single-phase overhead lines from the three-phase utility network can lead to system imbalance due to the uneven distribution of load among the phases. On the other hand, the multiple trains behave as nonlinear and time-varying loads and bring the harmonics, resonance and reactive power to the traction system, which represent one of the most significant sources of power quality distortion [18].

Renewable and ESS Integration - The integration of renewables and ESS into the railway traction power system has increased its complexity, leading to new challenges and concerns in the areas of system configuration, controller design, and benefit analysis.

Energy Efficiency Improvement - With the penetration of the power electronics, renewables and ESS, the power flow of the railway traction power supply system is more flexible, allowing further improvement of the energy efficiency on both the power supply and train operation sides. However, this is also a challenging task, requiring the development of advanced techniques and algorithms to manage the complex interactions between the different components of the system.

Safety and Reliability Enhancement - For railway operators, system safety and reliability have always been at the heart of the operational requirements. The integration of power electronics, renewables and ESS has raised more challenges to thermal management and device lifetime enhancement to guarantee longer term reliable system operation. Moreover, the inherent uncertainty of renewable generation due to the unpredictable weather conditions has also posed potential threats to the railway traction power supply system.

1.3 Research Motivations and Objectives

Along with the societal demand on low carbon transition to tackle the climate change and the target of achieving net zero by the mid of this century, railway electrification can play a critical role in carbon emission reduction in the transport sector. The arising challenges raised in last section are restricting the railway electrification development, which have drawn more attentions from all railway stakeholders. There is certainly an urgent need to address the above challenges. Targeting at these challenges, the following objectives will be addressed in this thesis:

- To improve the power quality and energy efficiency of the railway power supply system, targeting at the widely adopted co-phase railway power supply system with the power flow controller (PFC), it is necessary to conduct a comprehensive modelling analysis. Furthermore, flexible control schemes for power compensation will need to be developed and investigated to ensure optimal system performance.
- To effectively incorporate renewable energy into the railway power supply system, it is necessary to develop models of renewable-integrated railway power supply systems. These models will provide supports to the optimization of the power flow in the railway power supply system, taking into account the integration of renewable energy. Meanwhile, advanced optimization techniques and tools for the power flow is also necessary to be developed.
- To effectively integrate renewable energies while satisfying the demand from the highly varying traction loads, the benefits of integrating energy storage systems (ESS) into the railway power supply system needs to be investigated. Additionally, the reliability of the ESS integrated railway power supply system must be guaranteed by taking the energy storage management system into account in the system controller.
- To improve the energy efficiency of railway traction power supply system from the energy consumption side, the train movement dynamics need to be analysed and

the train trajectory has to be optimized considering its robustness.

1.4 Main Contributions of The Thesis

The contribution section of this thesis outlines the novel approaches and original contributions that have been made in the field of modelling, control and energy optimization for the railway traction power supply systems.

- A multi-objective optimization strategy based on NSGA-II algorithm has been proposed to reduce the system operation capacity while addressing the power quality issues for the co-phase system with renewable energy integration. A hybrid optimal compensation control scheme has also been developed to eliminate the negative sequence current caused by real-time prediction error.
- A DQN-based thermal constrained energy management strategy has been proposed for the railway co-phase system integrated with ESS. To constrain the thermal dynamics for both the power electronics modules and ESS and enhance their reliability, the overtemperature penalty terms are introduced in the problem formulation. The DQN-based method is adopted to learn an optimized policy for peak power shaving with the help of the ESS while meeting temperature constraints. Case studies confirm that the proposed strategy can effectively reduce the peak traction power supply by up to 42.0%, and achieve up to 94.1% temperature reduction for the power electronics modules and ESS. An FRA-based pruning method has also been proposed to make the agent more compact without compromising performance. It is confirmed the the FRA-based pruning can achieve up to 89.9% agent size reduction and 87.2% computation savings.
- A bi-objective robust optimization model has been formulated for the train speed trajectories to minimize both the energy consumption and journey time, in which the robustness against the uncertain train mass is also considered and viewed as a decision-maker (DM) preference. To handle the DM preference, a novel multi-

objective optimization algorithm namely p-NSGA-II has been proposed, incorporating the original NSGA-II and a proposed preference dominance criterion. The case studies have confirmed that the proposed p-NSGA-II can achieve up to 40.59% robustness improvement compared to the original NSGA-II.

1.5 Thesis Structure

The thesis is organised in six chapters and the relationship between each chapter is shown in Figure 1.2.

- Chapter 1 introduces the background of the importance of railway electrification, which serves to introduce the motivations behind this thesis. The main research purpose of this thesis is thus presented, which is to improve the energy efficiency of the railway traction power supply system considering various aspects.
- Chapter 2 reviews the literature related to electrified railway system, renewable and energy storage system development, and optimization techniques. The following chapters will investigate system-wide energy optimisation solutions which have not been fully studied.

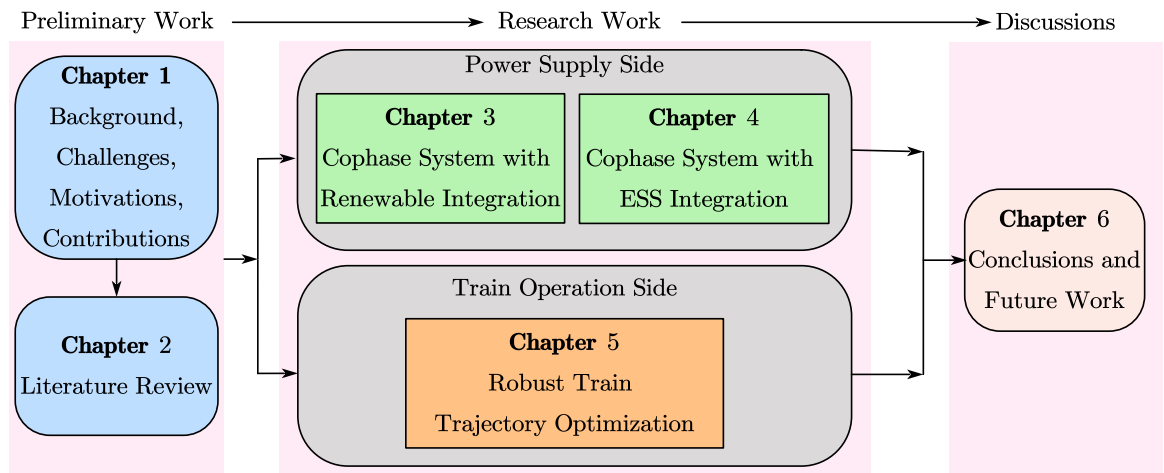


Figure 1.2: Thesis structure

- Chapters 3 and 4 target at the railway power supply side to investigate the optimal power flow control schemes considering the renewable and ESS integration. Chapter 3 investigates the renewable integrated co-phase railway power supply system. A multi-objective optimization method is adopted to optimize the power compensation schemes. Chapter 4 considers the ESS integration into the co-phase railway power supply system. A novel reinforcement learning framework is proposed to support the utility grid as well as enhance the reliability of the railway power supply system.
- Chapter 5 focuses on the train operation side to develop robust energy-efficient train speed trajectories. A novel robust multi-objective optimization method is proposed and a bi-objective robust train trajectory optimization model is formulated to minimize both the train energy consumption and journey time
- Chapter 6 concludes the thesis. The main findings and contributions of the research conducted in the previous chapters are summarised. Reflections and suggestions for future work are given.

LITERATURE REVIEW

2.1 An Overview of Railway Electrification

Different technological approaches developed during the time of railway electrification, as well as the specific economic nature of different countries adopted these technologies, have led to a variety of traction power supply configurations [19]. Ever since the emergence of electrified railway systems, various railway traction power supply modes, including direct current (DC) and alternating current (AC) modes, have been applied all around the world. Throughout the different eras, a variety of topologies were utilized to manage power transmission, voltage levels, and locomotive drive. These topologies and technological solutions continue to be used in modern times [20].

DC power supply traction systems operating at 600-750 V, 1500 V, or 3000 V are commonly used in suburban transportation services, such as trolley buses, trams, and metros. Although the configuration of the DC railway system is simple, the relatively low voltage is only suitable for light transport demand but not for long-distance high-speed railway. There are some examples for the DC railway systems [21].

- DC at 750 V in Paris, Montreal, Mexico City, Santiago, Lyon, and Marseille for

metros, and in Britain with third rail power supply;

- DC at 1500 V in Japan, France, Netherlands, and so on.
- DC at 3000 V in Russia, Italy, Poland, Spain, South Africa, Brazil, Belgium, and so on.

AC traction power system is a widely applied solution for long-distance electrified railway systems, as the high voltage of the AC railway traction system can significantly reduce power transmission loss compared to the DC system [22]. There also exist various AC railway modes, such as the AC system with 15 kV at the special frequency of 16.7 Hz, widely adopted in Germany, Sweden, Switzerland, Norway, and Austria, covering over 33,000 km of the single-phase European network in total. Another AC traction system is the 25 Hz frequency with 11-12 kV system, commonly used in the United States. Besides, the 25 kV/ 50 Hz AC traction system is widely used all around the world including Russia, France, Japan, China and so on.

In the UK, three types of railway traction systems are applied simultaneously: 25 kV AC overhead line system with 50 Hz frequency, 1.5 kV DC overhead line system and 650/750 V DC third rail system [23]. The overhead line standard of 25 kV/ 50 Hz was chosen by British Rail in the mid 20th century and has since become the predominant system throughout the country [24, 25].

Railway electrification is receiving much more attentions in recent years to meet the railway decarbonization target. The increased demand for the railway capacity has heightened the limitations of traditional systems in accommodating the higher power needed, while keeping reasonable costs [19]. According to the data published in 2021, the total route length of UK railway system is 15,935 km, of which 6,045 km of the mainline railway route has been electrified, accounting for 38% of all routes [10]. To achieve the target of full railway electrification by the year 2050, [11, 26] pointed out that 13,000 single-track kilometre routes need to be electrified, which translates to approximately 450 km of single track routes per year from now on.

Although some technical solutions such as battery power train or hydrogen powered trains are feasible to replace the petroleum-powered trains, they come with the downside of low technology maturity, occupying much onboard space, and adding extra weight to the vehicle. Currently, the AC electrified rail with overhead line is considered the highest energy-efficient solution among others [27]. Thus this thesis will primarily focus on the most widely applied 25 kV/ 50 Hz AC railway traction system.

2.2 AC Railway Power Supply Systems

2.2.1 AC Railway Power Supply Network Configurations

For the 25 kV/ 50 Hz AC railway traction power supply systems, various traction power supply network configurations were proposed and three widely applied configurations are briefly introduced below.

2.2.1.1 Direct power supply system

Direct power supply system is a simple feeding system as shown in Figure 2.1. The feeding currents flow through the overhead contact line and return to the rails directly [28]. However, the structure tends to generate a magnetic loop and cause significant electromagnetic interference to communication and control devices.

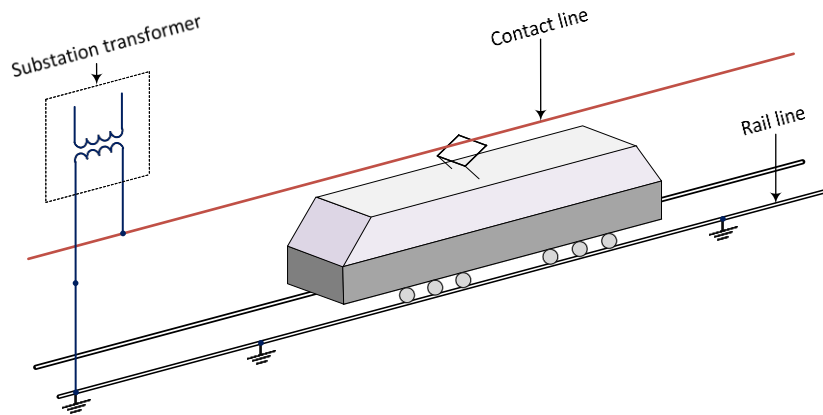


Figure 2.1: Direct power supply system

2.2.1.2 BT system

In AC direct power supply systems, the electric current is taken from the catenary conductor to the train, and fed to the earth-connected rails. However some portion of returning current may deviate around to the earth because of leakage of current from the track to the earth. This leakage current causes a heavy interference with the communication lines, metallic pipe-lines, bridges, etc. Therefore, it is required to avoid this interference by some means like booster transformer.

Boost-Transformer (BT) power supply system as shown in 2.2 is an effective way to handle the issues. The BT consists of windings of unity turn-ratio, i.e. booster transformer is a 1:1 transformer. The primary winding of the booster transformer is connected in series with the contact wire and the secondary winding is connected in series with the return current circuit. Therefore, the current flowing through the contact wire also passes through the primary winding of the booster transformer which induces current in the secondary winding in equal amount. This induced current in the secondary winding forces the return current to flow through only the return circuit and avoids the leakage of current to the earth and hence reduced the interference with the communication lines which are running near the track. The BT structure costs more than direct power supply system due to the extra investment of the booster transformers [29].

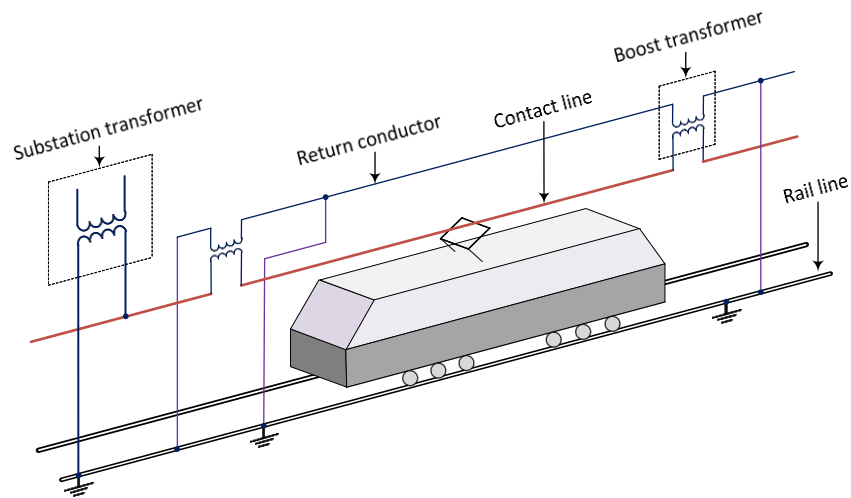


Figure 2.2: BT power supply system

2.2.1.3 AT system

Auto-Transformer (AT) power supply system is the most widely used AC traction system. The configuration of AT system is shown in Figure 2.3. The AT transformer is designed to reduce the transmission voltage from the high-voltage power supply 50 kV to the lower voltage 25 kV required by the catenary and feeder lines [19, 29]. The transformer accomplishes this by utilizing an earth-connected secondary central tap, which allows for the voltage to be adjusted at various points along the overhead line [19, 29]. The number of AT transformers required along the overhead line is distance-dependent, and their usage helps to improve the overall energy efficiency of the railway electrification system [19].

Compared to the direct power supply mode and BT mode with 25 kV voltage output, for the same traction power, the traction currents in AT system are reduced significantly. In this way, the power loss can be reduced and the feeding distance of each traction power supply section is prolonged.

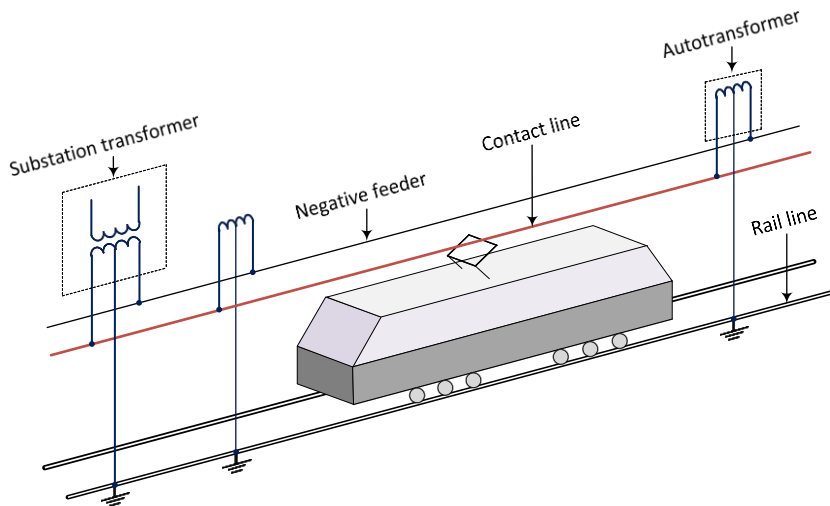


Figure 2.3: AT power supply system

2.2.2 Traditional Transformer-based AC Railway Power Supply Systems

Railway power supply systems play an important role in connecting the utility grid and the traction grid, and performing the power transmission and voltage transformation. A conventional railway traction power supply substation is usually composed of the traction transformer and corresponding protection devices [24]. The primary side of the traction transformer connects to the three-phase power grid, while the secondary side connects to the single-phase traction port, thereby enabling the transfer of power from the utility power grid to the traction loads. Based on the traction power requirements, the power rating of the substations is designed with levels ranging from 10 MVA to 75 MVA [30]. However, as power requirements increase, the power rating of substations can reach 80 MVA or even 120 MVA [31, 32]. To accommodate the various AC railway power supply network configurations described above, several topologies of the traction substations have been proposed. In the following, several typical traction transformers will be briefly illustrated as follows.

2.2.2.1 V/V and V/X Transformer

Figure 2.4 shows the configurations of V/V and V/X transformers widely used in the electrified railway systems. Amongst, the V/V transformer is preferred due to its simplicity in structure and connection. This configuration consists of two 25 kV single-phase transformers placed at each traction subsection connecting the catenary and the utility grid. As shown in Figure 2.4, both transformers are usually connected to different phases of three-phase utility grid in order to reduce the power imbalance.

However, this connection requires the installation of neutral sections inside each substation and between adjacent substations, which isolates the catenary grid into electrically isolated sections. This sectioning represents an obstacle to an efficient use of the energy, since the trains can only be fed by one substation at the same time resulting in reducing the use of regenerative braking energy among trains. Additionally, the

substation-inside auto-transformer is also required. The maximum allowed length of the power section is determined by the maximum voltage drop that can be tolerated in the catenary. Another configuration of V/X transformer has similar structure and characteristics to the V/V transformer. Compared to the V/V transformer, the V/X transformer can be directly used for the AT traction mode with no use of the substation-inside auto-transformer.

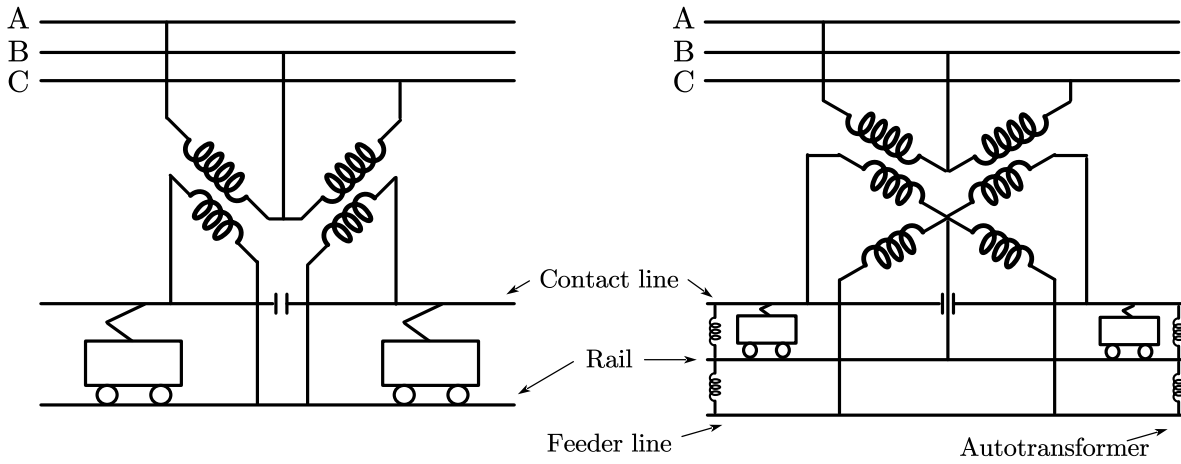


Figure 2.4: V/V transformer (left) and V/X transformer (right)

2.2.2.2 Balancing-feeding Transformer

To address the system imbalance and improve the power quality, the balancing-feeding transformers were developed. A balancing-feeding transformer is a type of power transformer that is specially designed to produce a balanced n -phase system from a balanced m -phase system [19]. In railway power supply systems, four most applied topologies are: Scott, Le-Blanc, Impedance matching and Woodbridge connection [33, 34]. Among them, Scott transformer, as a representative configuration, is introduced below.

As shown in Figure 2.5, the secondary side port β is coupled with phase AB . Port α is coupled with phase C and midpoint D of phase AB . The phasor diagram is shown in Figure 2.6. The voltage vector α in the secondary side is orthogonal to the voltage vector β based on the Scott connection. And the current relations can be derived as:

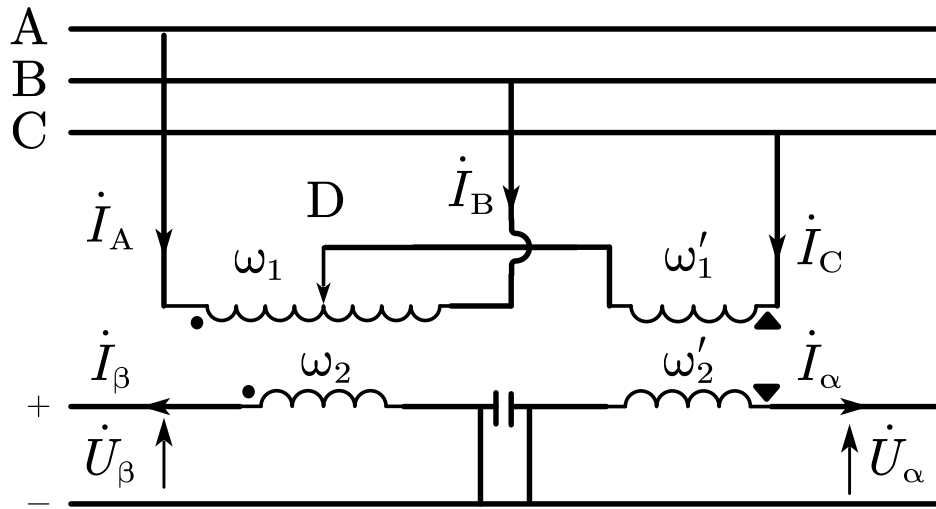


Figure 2.5: Scott transformer

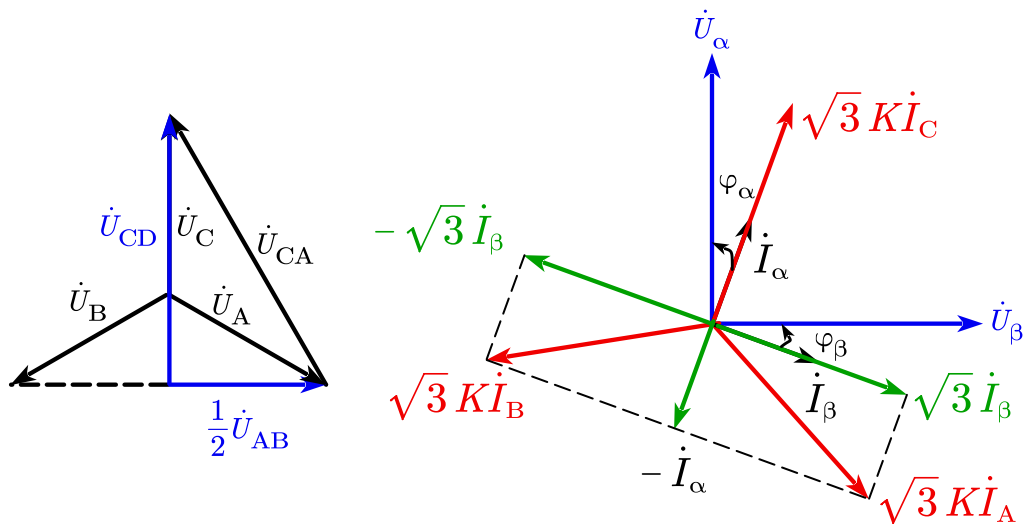


Figure 2.6: Phasor diagram of Scott transformer

$$\begin{cases} \dot{I}_A + \dot{I}_B + \dot{I}_C = 0 \\ \omega_1' \dot{I}_C = \omega_2' \dot{I}_\alpha \\ \dot{I}_A - \dot{I}_B = \frac{2\omega_2}{\omega_1} \dot{I}_\beta \end{cases} \quad (2.1)$$

Set $K = \frac{\omega_1}{\omega_2}$ and $\frac{\omega_1'}{\omega_2} = \frac{\sqrt{3}}{2}K$, the relationship between three-phase currents and sec-

ondary currents can be derived as :

$$\begin{bmatrix} \dot{I}_A \\ \dot{I}_B \\ \dot{I}_C \end{bmatrix} = \frac{1}{\sqrt{3}K} \begin{bmatrix} -1 & \sqrt{3} \\ -1 & -\sqrt{3} \\ 2 & 0 \end{bmatrix} \begin{bmatrix} \dot{I}_\alpha \\ \dot{I}_\beta \end{bmatrix} \quad (2.2)$$

If $I_\alpha = I_\beta$ and $\cos \varphi_\alpha = \cos \varphi_\beta$ are satisfied, the three-phase currents can be balanced, which is shown in Figure 2.6.

The other balancing-feeding transformers have the similar working principles as Scott transformer. However, it is essential to note that balancing-feeding transformers can only generate balanced three-phase loads if the two secondary phase currents are of equal magnitude. Additionally, the configuration of these balancing-feeding transformers are usually complex, with unequal numbers of turns on each limb, which can result in an unequal internal impedance of each limb and potentially cause the system imbalance even if both secondary phases are balanced [19].

2.2.3 Power Electronics Applications in AC Railway Power Supply Systems

Although transformer-based substations are the dominant technology for the railway traction at present, they suffer from strong drawbacks in terms of power quality. The main three issues for the traditional transformer-based substations are the power imbalances, low power factor and harmonic distortion [19]. Phase imbalances are still the main power quality problem for railway engineers even though the balancing-feeding transformers are applied. This issue results in negative sequence currents, and thus high short-circuit power electrical power supply systems are required to accommodate the power imbalances [35].

For either modern or conventional railway locomotives, their traction systems as well as the onboard ancillary services are significant sources of reactive power and harmonics in railway systems resulting in power distortion [36, 37]. As stated in [38], the power quality can be even worsened due to the possible resonances that are caused by

the high-frequency harmonics and further amplify the harmonics. Additionally, beyond the aforementioned power quality concerns, the electromagnetic emissions are another crucial factor to take into account.

Power electronics have brought new possibilities in various fields such as the electrical transportation systems [39–41] and the integration of renewable energy into the power grid [42]. The use of power electronics converters provides great potentials to eliminate or, at least, reduce the main power quality concerns found in traditional configurations. The most representative power electronic devices and systems are described below.

2.2.3.1 SVC

The static VAR compensator (SVC) represents a type of electrical devices which are combined with a series of thyristor-controlled reactors (TCRs) and thyristor-switched capacitors (TSCs)[43]. SVCs are designed to provide fast-acting compensation for reactive power to electricity transmission networks. The SVC is used to regulate voltage, power factor, and harmonics, as well as to stabilize the power system.

In railway power supply systems, SVCs can be installed on either the utility system side or the railway traction network side. However, the first option is typically preferred due to its simple control for compensating negative sequence current. Besides the negative sequence current compensation, SVCs also perform well in reactive power compensation and voltage regulation [44, 45]. It is essential to note that possible resonances between the SVC and power transmission networks should be considered [46]. Compared to other power electronics-based solutions, SVCs still have some natural limitations in meeting power quality requirements. Nevertheless, they remain a viable option when considering cost-effectiveness and simple control.

2.2.3.2 STATCOM

The static synchronous compensator (STATCOM) has evolved from SVCs and is widely used in electrical systems. In comparison to SVCs, STATCOMs can simultaneously handle the system imbalance, reactive power and harmonics due to the flexible power

conversion introduced by the fully controllable switches [47]. The application of a STATCOM in a railway power supply system is illustrated in Figure 2.7 (a). The STATCOM is installed on the three-phase side to achieve the power quality improvement. However, reactive power, negative sequence currents and harmonics can still flow through the traction transformer, increasing the risk of transformer failure [48].

2.2.3.3 Railway Power Conditioner (RPC)

The railway power conditioner (RPC) was initially developed by a Japanese scholar in 1993 and has since been used in practical applications [49, 50]. Unlike the STATCOM, the RPC uses a back-to-back converter and is installed at the secondary side of the traction transformer, as illustrated in Figure 2.7 (b). The RPC is preferred over the STATCOM because harmonics and reactive power do not pass through the transformer, reducing the impact of power quality issues on the traction transformers [51].

Another type of RPC structure, shown in Figure 2.7 (c), has also been proposed in Japan [52, 53]. Compared to the RPC structure in Figure 2.7 (b), this structure provides more flexibility for power sharing between two power supply sections, although the neutral section between them cannot be removed. This type of RPC has been found to be effective in compensating for negative sequence current and improving power quality in railway systems [54]. The control schemes for the RPCs have been comprehensively investigated and it has been confirmed that they are highly effective in enhancing the power quality even under distorted grid conditions [55–58].

2.2.3.4 Co-phase System

The aforementioned solutions primarily make use of two phase feeding connections in one substation that implies the neutral sections between two phases (power sections) are required no matter inside the substation or between adjacent substations. This presents a challenge for efficient energy utilization, as trains can only be powered by a single substation at a time, thereby limiting the potential for recovering regenerative braking energy among trains. The maximum section length is determined by the maximum volt-

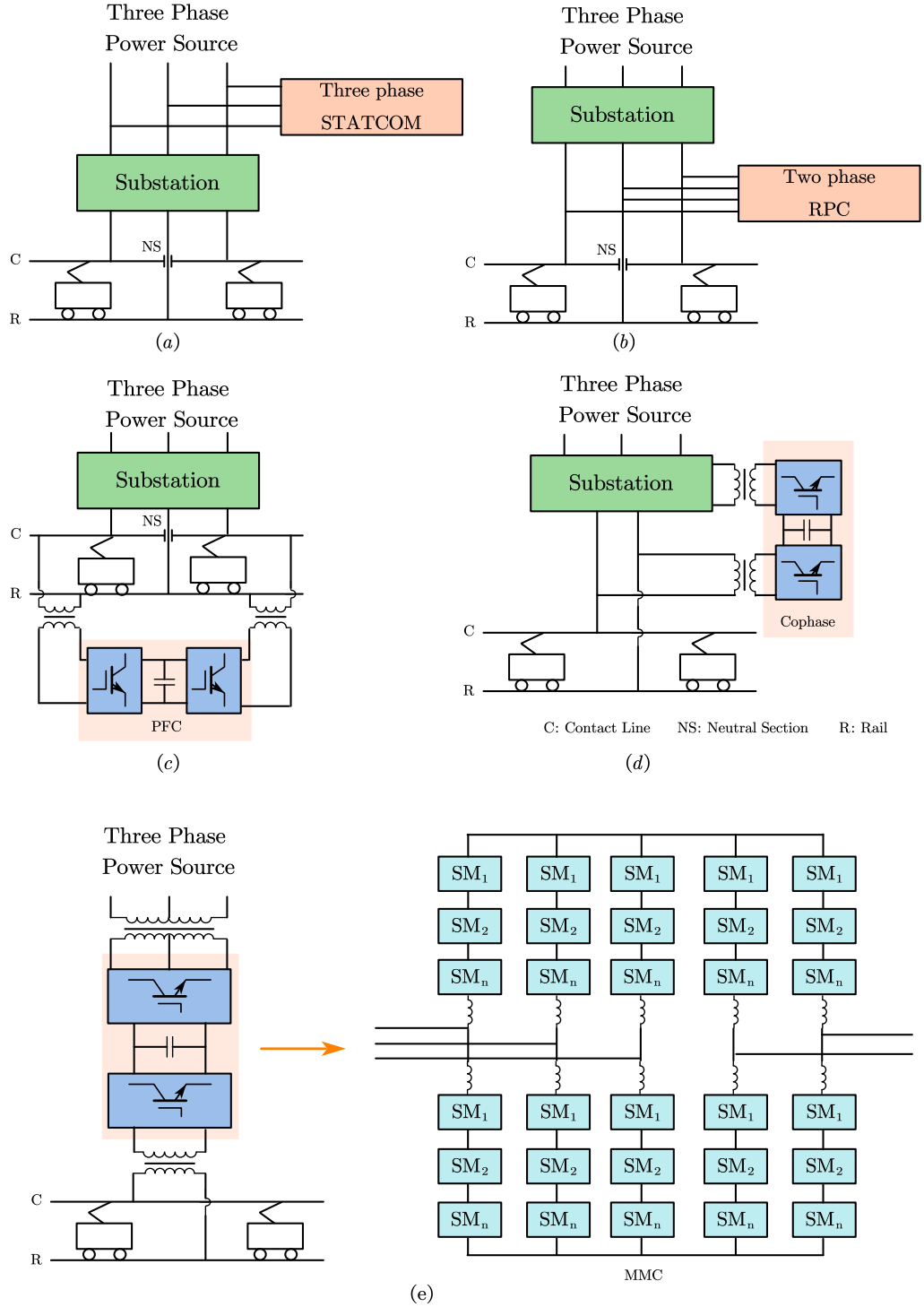


Figure 2.7: Power Electronics Based AC Railway Power Supply Systems. (a) STATCOM; (b) RPC1; (c) RPC2; (d) Co-phase System; (e) SFC (MMC) Based System

age drop admissible in the catenary. In order to increase this length, new configurations appeared and are demonstrated below.

In a study conducted by Southwest Jiaotong University in China, a compensation topology called the co-phase system was proposed as a solution to power quality issues [59]. The co-phase system employs a back-to-back converter connected to the traction transformer, as shown in Figure 2.7 (d). The back-to-back converter is referred to as either a power flow controller (PFC) [60], or hybrid power quality conditioner (HPQC) [61], but in this thesis, it will be referred to as PFC. This solution can partially address the problems caused by neutral sections, as the system can eliminate half of the neutral sections. The effectiveness of the co-phase system was demonstrated in a 10 MVA-rated system, and its compensation performance was verified [62].

Extensive research has been conducted on control schemes for the co-phase system. One study by researchers from Southwest Jiaotong University, as described in [59], focused on a full compensation scheme to achieve complete balance in the three-phase grid. However, a large power capacity of the PFC in cophase system is required under this full compensation scheme, which can be costly. Another research team from Macau University proposed a partial compensation scheme to address the issue of high operation voltage and reduce compensator capacity, as illustrated in [63, 64]. The control method for PFC in railway cophase system based on power quality requirements is discussed in [65], and the detailed design procedure and considerations for PFC operation to minimize operation voltage are detailed in [66]. Additionally, [67] and [68] describe the use of "impedance-mapping" techniques to maintain a low PFC operation voltage.

2.2.3.5 SFC Based System

The application of static frequency converter (SFC) in railway traction systems has become increasingly popular due to the latest advancements in power electronic devices. The SFC, typically implemented through modular multilevel converters (MMCs), allows for higher voltage and power ratings and can be directly connected to both the three-phase power grid and single-phase traction grid, as shown in Figure 2.7 (e). By regulating

the output voltage and phase angle, MMCs can control the power flow and eliminate the need for neutral sections between adjacent power supply arms. Although installing the PFC or replacing conventional transformers with MMCs can lead to a significant increase in construction costs, the use of controllable power electronic devices provides flexibility for energy flow and great potentials for the energy efficiency enhancement.

SFC has been successfully implemented in substation construction in various countries. Early applications of railway SFC in the United States date back to the late 20th century, with a system installed in Philadelphia operated by the Southeastern Pennsylvania Transportation Authority [69]. In Japan, SFC has been applied in Tsunashima, Nishisagami, and Numazu for the purposes of energy saving [70]. The Queensland rail network has investigated SFC applications in Australia [71]. The Wulkuraka feeder station is one example of SFC applications in Queensland Railway, with a capacity of 20 MVA as demonstrated in 2015 [26]. It has been confirmed that SFC technology can reduce operational and maintenance costs, while improving the system efficiency and stability [26]. In the UK, the first application of SFCs was agreed as part of the 'East Coast Power Supply Upgrade' project. Two SFCs were installed at Hambleton and Marshall Meadows respectively, both having 132 kV connections. Another SFC feeder station has been commissioned at Doncaster, connecting the 33 kV utility grid [72]. Additionally, for the railway power supply system at 16.7 Hz adopted in Germany, Austria, Switzerland, Sweden, and Norway, the SFCs can potentially replace the traditional cycloconverters which can convert a specific constant frequency AC waveform to another AC waveform of a lower frequency without DC link. While using SFCs with intermediate DC link can bring more advantages such as easy cooperation with other substations and power compensations for active and reactive power output [73].

For the aforementioned power supply techniques applied in railway traction power supply systems (TPSSs), their respective characteristics are summarized in Table 2.1.

Table 2.1: Comparisons of Power Supply Techniques in TPSSs

Type	Pros	Cons
Transformer-based TPSSs		
V/V and V/X transformers	1 Simple connection 2 Low investment 3 High system stability	1 System imbalance 2 Reactive power and harmonics 3 Uncontrollable power flow 4 Neutral sections required
Balancing-feeding transformers	1 Low system imbalance 2 Low investment 3 High system stability	1 Complex connection 2 Reactive power and harmonics 3 Uncontrollable power flow 4 Neutral sections required
Power electronics applications in TPSSs		
SVC	1 Medium investment 2 Reactive power compensation and harmonics elimination 3 Simple control	1 System imbalance 2 No active power flow control 3 Neutral sections required
STATCOM	1 Medium investment 2 System balancing 3 Reactive power compensation and harmonics elimination	1 Only functioning on the three phase side 2 Neutral sections required
RPC	1 Medium investment 2 System balancing 3 Reactive power compensation and harmonics elimination 4 Flexible power flow 5 Renewable integration	1 Complex control 2 Neutral sections required
Co-phase system	1 System balancing 2 Reactive power compensation and harmonics elimination 3 Flexible power flow 4 Reduction of half number of neutral sections 5 Renewable integration	1 Complex control 2 Adjustment of current system connection
SFC based system	1 System balancing 2 Reactive power compensation and harmonics elimination 3 Flexible power flow 4 No neutral sections required 5 Renewable integration	1 Complex control 2 Replacement of existing system 3 High investment

2.2.4 Smart Railway Power Supply Networks with Renewable and ESS Integration

In recent years, developing sustainable energy systems has become a global trend, and it requires maximal utilization of renewable energies while providing secure and reliable power to end-users from aspects of energy generation, transmission, and distribution [74].

The smart grid (SG) concept as an important technical branch of the next generation electrical network has presented significant opportunities for reducing carbon emissions, energy consumption, and operation costs, as well as improving energy efficiency, and enhancing system stability and reliability. The smart grid has paved the way for the integration of advanced low carbon technologies, such as distributed energy resources (DERs), hybrid energy storage system (HESS), and microgrids (MGs) [74].

However, despite the significant progress of SG applications in the utility grid, its implementation in electrified railway systems (ERSs) has been less straightforward, regardless the fact that ERSs have dedicated equipment, and transmission and distribution lines that make them suitable for integrating SG technologies. Since the rail traffic is expected to increase in the near future, the delayed incorporation of SGs in ERSs has posed a challenge of increased energy costs due to the surge in energy demand. It is therefore necessary to make changes in the way of energy consumption in the railway system to address this challenge. The optimization of railway power supply system performance can be achieved by introducing the SG and MG technologies to establish smart railway power supply networks. Meanwhile, rather than rebuilding the existing railway infrastructure, further investigation is needed to determine the optimal integration points and structures for incorporating SG and MG technologies [74].

The potential benefits of aforementioned technologies have prompted motivations to explore the feasibility and various integration solutions for DERs such as PV panels and wind turbines, the regenerative braking energy (RBE) in combination with railway power flow controllers, and the energy storage systems (ESSs). Furthermore, the development of advanced power supply substation technologies with integration of high-voltage power

electronic devices has also been investigated to enable new functionalities and enhanced control of power flow. These developments can potentially increase the reliability, resiliency, efficiency, and flexibility of railway power supply systems. The railway power supply substations with integration of power electronic devices, DERs and ESS can be seen as 'smart grid nodes'. The multiple railway smart grid nodes are also capable of providing system benefits and support the evolution of the utility grid.

In the following, various smart AC railway microgrids (ARMGs) are examined, together with the concept of the smart railway energy hubs as the foundation for future railway traction power supply system, to provide a path to integrate the smart grid (SG) technologies in the railway sector. There are two main architectures for integrating microgrids (MGs) into AC railway traction power supply systems: AC railway microgrid (ARMG) and hybrid ARMG [74]. In the ARMGs, distributed energy resources (DERs) and energy storage systems (ESSs) are directly connected into and shared with a common AC busbar provided by the existing AC railway power supply systems. The energy from either utility grid, DERs or regenerative power from trains to the loads such as tractive loads and substation internal loads can flexibly pass through the interfaced AC busbar with the help of the distributed converters, functioning as a railway energy hub. In the hybrid ARMG, DERs, ESSs and other components are aggregated into a DC busbar as an energy hub. The interaction between the DC busbar and AC railway power supply system can be achieved through the specific interfacing converters, which not only serve the purpose of power flow management but also help mitigate power quality issues [74].

2.2.4.1 ARMG

Figure 2.8 (a) shows the ARMG system, which is expanded on the basis of the traditional railway traction power supply system. As mentioned, all DERs and components are directly connected to the existing AC busbar. The AC busbar, as the interface of the railway energy hub, can be built in two different positions, either near the power supply substation or along the railway line.

- 1) Near the power supply substation: This solution is commonly used since DERs and

ESS can be installed in the same buildings as the substation, so that some switching and protection devices can be shared instead of making extra investments. Additionally, being close to the utility grid enables greater power flow. An example of this configuration is the solution proposed in Japan, with PV panels installed on top of the substation roof [75].

2) Along the railway line: The second option is to establish the AC busbar along the railway line. Although this approach can be more challenging to implement, it offers the advantage of being able to capture more renewable energy sources distributed along the railway line. Furthermore it has the potential to provide extra power support for weaker points in the railway traction networks.

2.2.4.2 Hybrid ARMG

In order to increase the flexibility of power flow, and overcome power quality limitations in ARMG, various hybrid ARMG structures have been proposed. These structures incorporate an interfacing DC busbar to achieve the integrations of various DERs and ESSs. The hybrid ARMGs can be subdivided into four main configurations: IFC-based hybrid ARMG (Figure 2.8 (b)), railway power conditioner (RPC)-based hybrid ARMG (Figure 2.8 (c)), Cophase hybrid ARMG (Figure 2.8 (d)) and SFC based ARMG (Figure 2.8 (e)).

1) Hybrid ARMG with IFC

The structure of IFC-based hybrid ARMG is shown in Figure 2.8 (b), which is taking advantage of IFC to achieve the connection between the AC and DC buses. Various DERs and ESSs can be integrated into the DC busbar directly without AC power conversion. The flexible bidirectional power flow between AC and DC buses can be realised through the IFC as a bridge with corresponding control methods. In this way, the MG can be introduced into the original railway power supply substation.

Limitations: Since the connection of all DERs and ESSs to the railway power supply system is dependent on the IFC, the control of power conversion for IFC becomes complex. When integrating DERs and energy storage systems, the converter must handle multiple input sources. It also needs to manage multiple output loads and energy storage devices.

2.2. AC RAILWAY POWER SUPPLY SYSTEMS

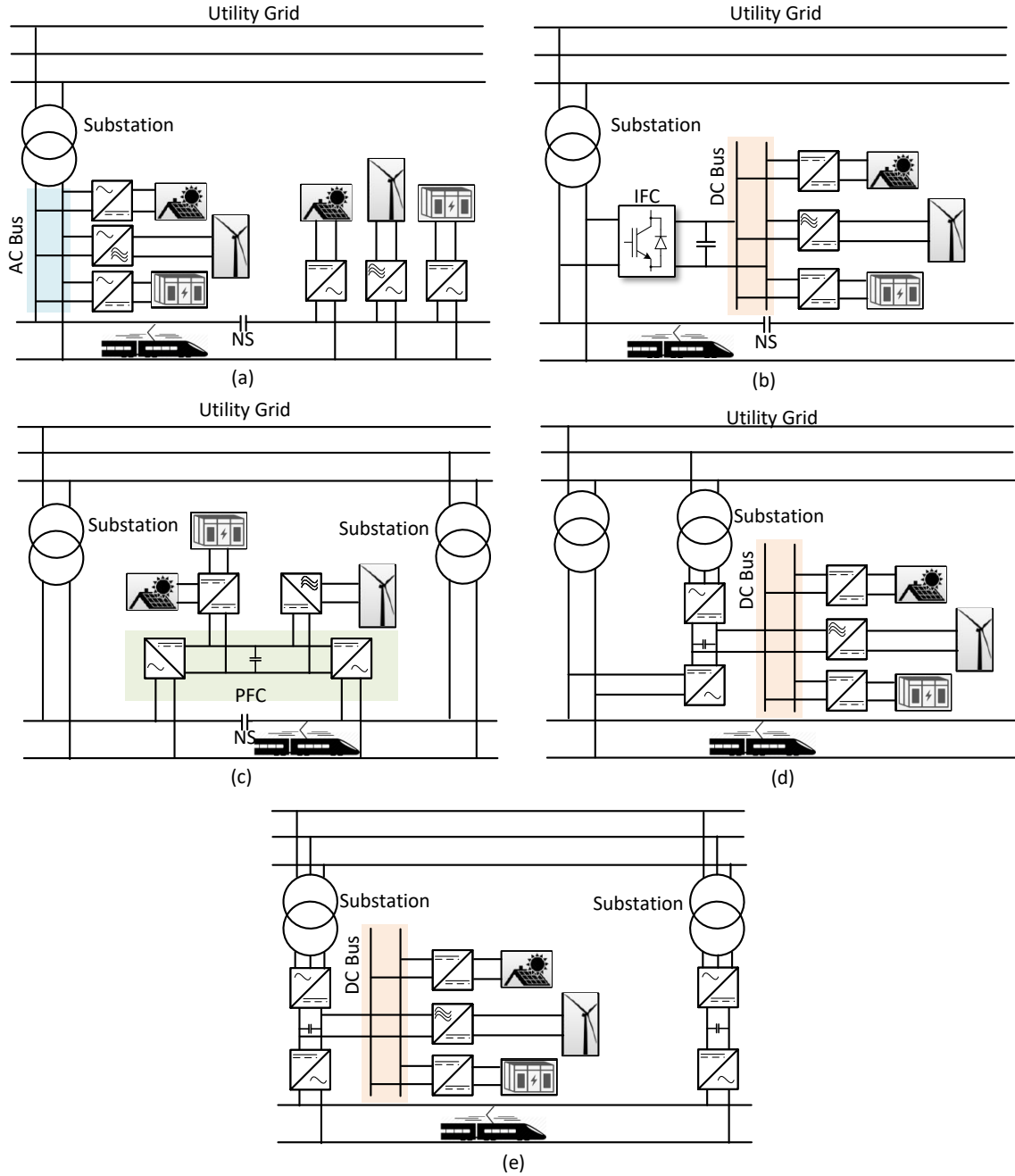


Figure 2.8: Smart Railway Power Supply Systems. (a) ARMG; (b) Hybrid ARMG with IFC; (c) Hybrid ARMG with RPC; (d) Cophase hybrid ARMG; (e) Hybrid ARMG with SFC;

Coordinating and optimizing the power flow among these diverse inputs and outputs can increase the control complexity. And integrating DERs and energy storage systems requires the converter to regulate voltage and frequency levels to maintain grid stability

and quality. This involves monitoring and controlling the converter's output voltage and frequency to match grid requirements and respond to dynamic changes in load and generation. The converter also needs to communicate with the grid and other control systems to exchange information, respond to grid signals (such as frequency and voltage deviations), and ensure seamless integration with the utility infrastructure. These factors will increase the complexity of the control. Additionally, since the IFC acts as the only interface connecting the AC and DC sides, the system's robustness becomes challenging. Furthermore, the IFC-based hybrid ARMG is not capable of handling system imbalance since it is only functioned in one power supply section.

2) Hybrid ARMG with RPC

To overcome the limitations of IFC-based hybrid ARMG, the RPC was proposed and can be applied across the neutral sections between adjacent two power supply stations as shown in Figure 2.8 (c). The RPC consists of a back-to-back converter with a shared intermediate DC link. The DC link serves as an interface to connect the DERs and ESSs, and thus a multiterminal DC railway energy hub can be realised. Leveraging the inherent capabilities of this RPC based configuration, the reactive power compensation and harmonic elimination can be achieved for two adjacent power supply sections. Meanwhile, the RPC provides the bidirectional power flow, which helps to handle the power imbalance between adjacent power supply sections, and also enables the transmission of RBE to neighboring power supply sections.

Limitations: Although the RPC-based hybrid ARMG can share the power between adjacent power supply sections, the neutral section issues can still not be eliminated. And the power level is confined by the capacity of the DC link in the RPC unless implementing high-cost multilevel RPC.

3) Hybrid ARMG with Cophase System

The cophase Hybrid ARMG, as shown in Figure 2.8 (d), is mainly comprised of a traction transformer with a back-to-back converter, which is also called as power flow controller (PFC). Similar with the hybrid ARMG with RPC, the railway cophase systems provide the DC busbar integrated in the back-to-back converter as the interface to the

DERs and ESSs as shown in Figure 2.8 (d). Moreover, this solution can reduce neutral sections by half the number. With aid of DERs and ESSs, the railway co-phase system can not only handle the system imbalance and power quality issues, but potentially provides extra supports for the utility grid.

Limitations: The railway cophase system can still not fully overcome the issues raised by the neutral sections.

4) Hybrid ARMG with SFC

The hybrid ARMG with SFC, as shown in Figure 2.8 (e), is composed of step-down transformer, SFC (typically a modular multilevel converter - MMC), DERs and ESSs. Since the power frequency and phase angle can all be regulated by MMC, and intermediate DC busbar inside MMC exists, the hybrid ARMG with SFC can not only fully eliminate the neutral section but also facilitate the absorption of DERs and integration of ESSs [76]. Consequently, this allows the power supply substations to achieve symmetrical power supply, thereby providing support for the utility grid.

Limitation: This proposed solution necessitates the replacement of the traditional transformer-based substation by the SFC resulting in a significant increase in cost. And the system control will be more complex due to the flexible power flow without neutral sections.

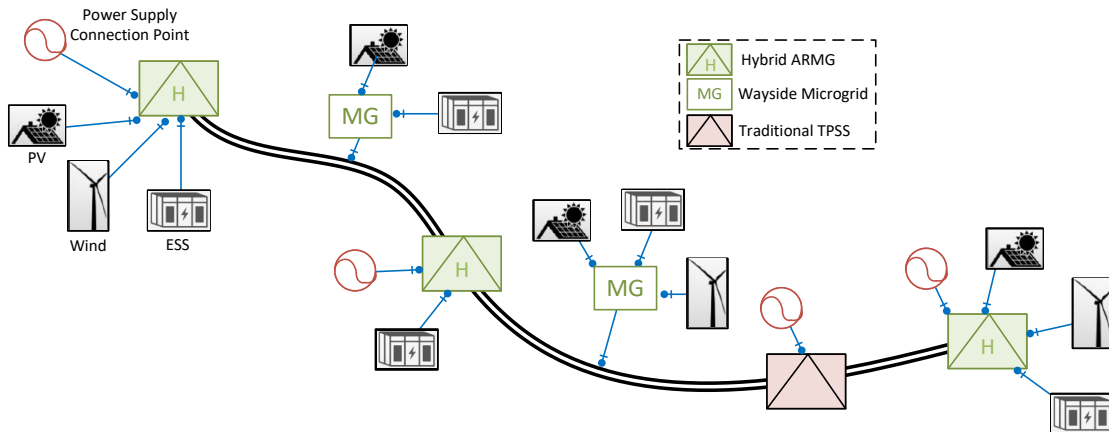


Figure 2.9: Schematic diagram of flexible smart traction power supply system.

2.2.4.3 Future Trend of Traction Power Supply Network

The future railway power supply network will likely consist of multiple "smart railway energy hub nodes", where DERs and ESSs are integrated to establish a flexible and smart traction power supply system (FSTPSS), as shown in Figure 2.9. The nodes can be of the same type or of different types of the structures discussed above. While the power supply mode should be either AC or DC. For example, the smart railway energy hub node can be a SFC based ARMG. Moreover, to leverage various wayside distributed generation options, MGs can be established along the traction lines and connected to the traction network through a DC-AC converter. These wayside regional MGs, also as a type of "smart grid nodes", can aggregate ESSs and wayside distributed generators. The incorporation of regional MGs with the railway network not only enhances the power supply capacity of the traction power supply system but also captures the regenerative braking energy of the locomotive for regional use.

2.3 Train Traction System

DC and AC electric motors are widely used in railways, no matter the traction supply is DC or AC [77]. Although power supply standards may vary across different parts of the world, the traction propulsion systems in specific rolling stocks are similar. Modern power electronic devices offer smooth power flow that is suitable for different types of traction motors. This section briefly reviews the electric train propulsion systems and technical advancements in train traction systems.

2.3.1 Current Propulsion Systems

Based on the propulsion mode, train traction systems can be classified as concentrated and distributed traction systems as shown in Figure 2.10. For the concentrated traction systems, the configuration applies two motorized vehicles at both ends of the train with non-tractive trailer vehicles in between. Only the motorized vehicles can provide the tractive force for the entire train. In comparison, the distributed traction systems in-

cludes several motorized electric units. The tractive power is provided by the distributed motors inside electric multiple units (EMUs). Comparing with concentrated and distributed traction systems, both energy consumption per passenger and train weight of concentrated traction system are higher than those of distributed traction system [78]. Furthermore, the distributed traction system has the better performance over the concentrated traction system in terms of acceleration due to its higher tractive effort. However, the movement control for the EMUs is more challenging in terms of assigning the power distribution [79].

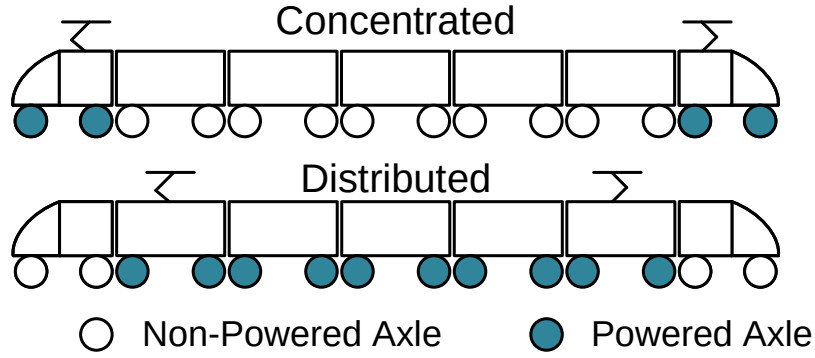


Figure 2.10: Classification of train traction systems.

The configuration of the typical EMU traction drive system is shown in Figure 2.11, where the traction power is collected from the AC overhead line through pantograph. The voltage is reduced by a on-board transformer and regulated by a four-quadrant back-to-back converter to fit the traction motors [80]. As shown in Figure 2.11, one converter usually feeds a group of motors simultaneously. Benefiting from the back-to-back converter, the power is able to flow bidirectional, which provides possibility to save energy from the braking regenerative power. The excessive regenerative power will be dissipated through braking resistors [81].

2.3.2 Trend of Advanced Techniques in Train Traction Systems

The voltage conversion inside the train is typically carried out by an on-board transformer. The traditional on-board transformers occupies around 12% of the vehicle's total volume, which reduces the space available for passengers [79]. To address this limitation, the

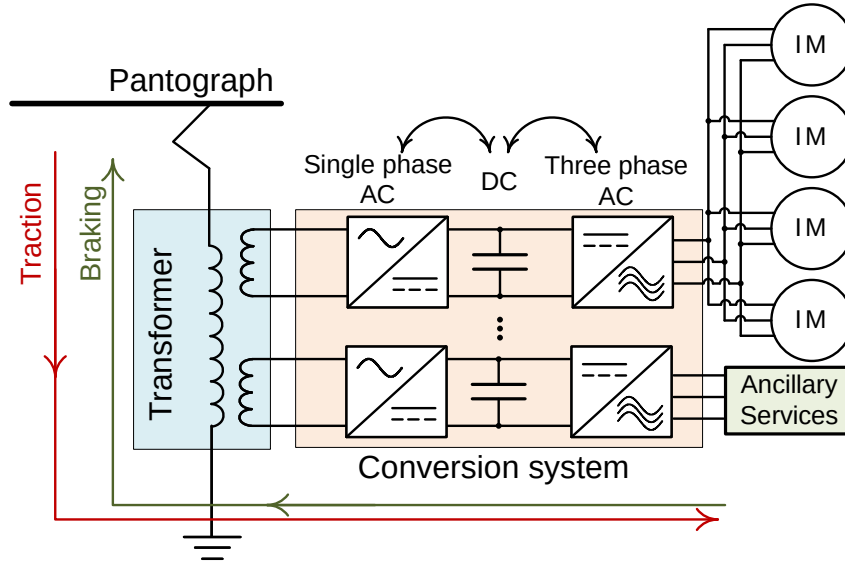


Figure 2.11: Traction drive system.

power electronic transformer (PET) is an alternative solution. By employing the power electronic techniques, the power frequency is increased to a high level, resulting in a smaller volume compared to the traditional on-board transformer [80]. With the advancement of PET, the efficiency of PET has been close to or even exceeds that of traditional transformers, reaching up to 96.5% [82]. However there are still some challenges in terms of topology design, thermal management and cooling system [79]. Besides, the motor design is another aspect affecting the train operation performance. The pursuing for higher power density and efficiency of the motors offers great potentials to make a more compact bogie. Some efforts have been done in [83–86]

Another attractive application is the on-board ESS which provides more flexibility for the on-board power flow. Typically, the excessive braking regenerative power is fed back to the overhead line and can be utilized by the adjacent trains or absorbed by the utility grid. However, this approach is not always ideal, as some of the regenerative power can be wasted during the transmission process. Moreover, it can be difficult to regulate the unexpected energy input into the utility grid. With on-board ESS, instead of being wasted or transmitted back to the grid, the regenerative power can be stored within the train and utilised later [87–89]. Moreover, trains equipped with an on-board ESS can operate on rail sections without an overhead power supply, since they can draw

from the stored energy in the ESS [90, 91]. However, as the ESS weight and volume significantly affect the energy efficiency, oversizing might unnecessarily increase the weight and volume of on-board ESS, which will occupy the onboard space for passengers and increase its traction energy consumption. While undersized could be critical for energy efficiency [92, 93]. Additionally, the operation power of the train is high and fluctuated frequently. The requirements of the charging/ discharging rate of onboard ESS are high. The thermal and safety considerations also raise concerns for the on-board ESS applications [94].

2.4 Energy Optimization Techniques for Railway Traction Power Supply Systems

A comprehensive review of energy optimization techniques for AC railway traction power supply systems is conducted. In section 2.4.1, basic optimization techniques are briefly introduced. In section 2.4.2, optimization applications for the railway power supply system and train operation are reviewed respectively.

2.4.1 Optimization Techniques

For a general optimization problem, the formula can be expressed as follows:

$$\begin{aligned} \min \quad & f(x) \\ \text{s.t.} \quad & h(x) \leq 0 \end{aligned} \tag{2.3}$$

where x represents the decision/ control variables. $f(x)$ is the objective functions and $h(x)$ denotes the constraints. $f(x)$ and $h(x)$ can be either linear or nonlinear, constituting the linear and nonlinear optimization problems respectively. Obviously, there is no single method for solving all these problems. For different types of the optimization problems, the specific optimization techniques are introduced below.

2.4.1.1 Conventional optimization methods

The most widely used conventional optimization methods include linear programming (LP) [95, 96], integer linear programming (ILP) [97–99], quadratic programming (QP) [100, 101] and dynamic programming (DP) [102, 103].

Linear Programming - Linear programming, also known as linear optimization, is a technique for solving optimization problems with linear objectives, also subject to linear equality and inequality constraints [95, 96]. The feasible region for a linear programming problem is convex, and the objective function is a linear function defined on this convex region. A linear programming algorithm is used to find a point within the convex region that minimizes or maximizes the objective function [96].

Linear programming (LP) has several desirable characteristics. Firstly, it is theoretically reliable for finding optimal solutions due to its convergence properties. Secondly, it is computationally efficient, with fast convergence and low resource requirements. LP is widely used in real-world engineering applications because many optimization problems, such as optimal power flow [104, 105] and economic dispatch [106, 107], can be formulated as linear problems. The simplex method and interior point methods are two effective LP methods. However, LP techniques cannot directly solve the widely existing nonlinear problems, unless they are first linearized using approximation techniques.

Integer Linear Programming - Integer linear programming (ILP) problems can be seen as a special form of the LP problems with some or all decision variables being integers [97–99]. A specific instance of ILP, known as 0-1 integer linear programming with binary decision variables, is usually formulated for the on/off decision in some engineering optimization applications [99]. If both continuous and discrete variables exist simultaneously, the problem is known as a mixed-integer programming problem (MILP) [99, 108].

The straightforward idea to solve an ILP problem is to first remove the constraint with integer decision variables, and find the corresponding LP problem after relaxation. Then

the solutions are rounded to satisfy the constraints for the integer decision variables [99]. However, it is highly likely that this approach leads to suboptimal solutions or constraint violations. One set of algorithms which can solve the ILP problem exactly are cutting plane methods [99, 109]. The principle is to solve the relaxed ILP and then consider the linear constraints so as to move towards the integer solutions without violating the constraints [99].

Quadratic programming - Quadratic programming (QP) problem is a special type of nonlinear programming problems with a multivariable quadratic objective function subject to the linear constraints on the variables [100, 101]. The model predictive control is a typical application of the quadratic programming.

Generally, the LP techniques hardly handle the the quadratic programming problems due to its nonlinearity unless the problems can be converted into a LP formulation based on the Kuhn-Tucker condition. A variety of algorithms to solve QP problems includes interior point method, augmented Lagrangian method and gradient projection method [101]. Some commercial tools with mature solvers applicable for solving the LP, ILP and QP problems, such as CPLEX, GAMS and Gurobi, are efficient and have been popular in both academia and industry.

Dynamic programming - Dynamic programming is a mathematical optimization method developed by Richard Bellman in the 1950s and has diverse applications in various areas [102, 103]. This method simplifies complex problems by dividing them recursively into sub-problems that are easier to solve. If each sub-problem is solvable, the original problems can also be solved recursively by leveraging the relationship between the sub-problems and the original problem [102, 103].

2.4.1.2 Meta-heuristic optimization methods

Meta-heuristic optimization is a remarkable field of research that has made significant advancements in solving both linear and nonlinear optimization problems that are challenging to solve. The optimization problems that meta-heuristic approaches have

tackled cover a wide range, from single-objective to multi-objective, from continuous to discrete, and from constrained to unconstrained. Typically, solving these problems can be complicated due to their complex behavior [110].

Most of the current cutting-edge meta-heuristic algorithms were originally developed prior to the year 2000, such as Genetic Algorithms (GA) [111], Particle Swarm Optimization (PSO) [112] and Ant Colony Optimization (ACO) [113] for single objective optimization problems, and Non-dominated Sorting Genetic Algorithm-II (NSGA-II) [114], NSGA-III [115] and Strength Pareto Evolutionary Algorithm 2 (SPEA-2) [116] for multi-objective optimization problems. New algorithms and variants of existing ones are continuously being developed for now, due to the superior features of these meta-heuristic algorithms:

- **Stochasticity:** Meta-heuristic algorithms typically involve stochastic searching processes, meaning that they randomly explore broader feasible region and tend to escape from the local optima. This enables them to have more chances to find optimal solutions.
- **Technique combination:** Meta-heuristic algorithms provide a superior framework combining and taking advantage of various optimization techniques, such as global search and local search, to balance the exploration for broader region and the refinement of the best solutions found so far.
- **Flexibility:** Meta-heuristic algorithms can be applied to a wide range of optimization problems, such as single-objective and multi-objective optimization, continuous and discrete optimization, linear and nonlinear optimization, and constrained and unconstrained optimization problems.

2.4.1.3 AI-based optimization methods

As artificial intelligence (AI) has advanced, AI-aided optimization techniques have proven efficient in overcoming the bottlenecks of complex problems. There are various sub-fields of AI, such as machine learning, deep learning, computer vision, natural language

processing, and robotics. This section will briefly introduce two commonly used AI-based techniques, namely deep learning (DL) and reinforcement learning (RL).

Deep learning (DL) derived from the artificial neural networks (ANNs) has the ability to learn from large datasets with complex dynamics and extract relevant features in a short time using high-performance computational devices [117]. As a result, it has a wide range of industrial applications, including behavior prediction, system modeling, image identification, and object classification [117]. DL is capable of modelling both linear or nonlinear systems only based on the data, even when the data is limited. Unlike traditional physics-based approaches, DL uses data-driven methods without the need for explicit knowledge of the physics [117, 118].

Deep learning (DL) has had a significant impact on the field of energy optimization, especially in relation to power grid management [119]. One area where DL has shown effective is in prediction problems, such as the power output prediction of photovoltaic (PV) systems [120, 121], energy demand forecasting [122, 123] and state prediction of power system [124]. In [125], DL was used for the modelling of demand side response, which results in a higher accuracy compared to the conventional modelling methods.

RL is a branch of machine learning, in which the agent learns the optimized policy through a trial-and-error process [119]. During the training process, the agent initially takes actions randomly in each trial, and then it modifies its future actions based on the rewards and consequences it receives from its current actions within the environment [119]. The primary aim of the training is to drive the agent to interact effectively with the external environment and receive the maximum reward possible [119].

Inspired by the advancements of the DL, an effective approach namely deep reinforcement learning (DRL) has emerged by combining DL and RL. Deep reinforcement learning, through the generalization capabilities of deep neural networks and the search policies provided by reinforcement learning, has played a significant role in the fields of optimization and decision making. The characteristics of DRL can be summarized as [119, 126, 127]:

- **Real-time Adaptability:** Deep reinforcement learning algorithms can quickly adapt

to changing environments in real-time and make decisions accordingly. This makes DRL particularly useful in dynamic and uncertain situations.

- **High-dimensional Inputs:** DRL can handle high-dimensional inputs, such as images and various system states, allowing it to tackle complex problems that may not be solvable using traditional optimization methods.
- **Unsupervised Learning:** DRL can learn from experience without explicit supervision, making it well-suited for problems where the optimal solution is unknown or difficult to define.
- **Reward-based Optimization:** DRL algorithms use a reward-based system to optimize decision making, which allows the algorithm to learn from the experiences and improve with training going ahead, making it ideal for applications where the optimal solution may change over time.

In this thesis, a DRL-based thermal constraint energy optimization framework is proposed in Chapter 4. Additionally, a comprehensive review for the DRL applications in energy optimization is also presented in Chapter 4.

2.4.2 Energy Optimization for Railway Traction Power Supply Systems

The energy used for traction accounts for around 60% to 70% of total railway energy consumption [128]. Therefore, the topic of optimizing and improving the energy efficiency of the whole traction power supply system is of theoretical and practical significance. The energy efficiency is determined by various factors, such as types of power sources, power transmission losses, train driving styles, and vehicle characteristics. The considerations of improving the energy efficiency for the entire railway traction power supply system primarily focuses on two aspects: 1) power supply side including the integration of DERs with ESS, reduction of transmission of power loss, enhancement of system reliability;

and 2) train operation side including the timetable scheduling, train speed trajectory optimization. A review for these two parts are conducted as follows.

2.4.2.1 Energy Optimization for Railway Power Supply Systems

Regarding the power supply side, as aforementioned, the development from traditional transformer based substations to modern power electronics integrated substations has resolved the main power quality issues. The elimination of these power quality issues such as reactive power and harmonics has significantly enhanced the energy efficiency of the power railway power supply system.

Even with the advancements in power devices and topologies, the optimization of control for the energy flow throughout the power supply substation is another driving factor towards increasing energy efficiency. For example, in [129], for the co-phase railway power supply system, an improved coordinated control strategy that can alleviate thermal stress is proposed to reduce the degradation of the power electronic device and enhance the system reliability. In [130], a novel co-phase configuration of the traction power supply system (TPSS) which is structured with VX-connection traction transformer (TT) and power flow controller (PFC) adopting the modular multilevel converter (MMC) topology is presented. A hierarchical control strategy with upper PQ compensation optimization algorithm and low-layer PFC control is designed. It is confirmed that the proposed co-phase TPSS is able to reduce the compensation capacity by up to 59%. Also in [131], for the railway power flow controller (RPFC), an optimization strategy considering system capacity and operating performance improvement is developed. The strategy not only enables a railway substation to meet the grid-connection standards with high computational efficiency, but also renders the RPFC to have the minimum design capacity and excellent feeder voltage control ability,

Meanwhile, the integration of renewable and ESS into power supply system offers great potentials to enhance the system energy efficiency. This has resulted in a more flexible and complex energy flow within the railway power supply system. Thus, regarding the aspects such as system design and sizing, energy dispatch and management, and

system reliability enhancement, the optimization plays a critically important role. For example, in [132], driven by the day-ahead forecast information of traction power, a dynamic voltage unbalance regulation strategy was proposed by coordinating the power distribution among the ESS, power flow controller, and traction transformer. In [133], a flexible traction power supply system (FTPSS) was proposed to provide flexible interfaces for hybrid energy storage system and photovoltaic. With the proposed hierarchy energy scheduling method, the system operation cost reduction can reach up to 13.6%. In [134], a robust energy management strategy for the railway co-phase system considering the uncertainties of the PV and traction load was proposed to reduce the system operational cost. More research work on railway power supply system optimization with renewable and ESS integrated also can be found in [76, 133–136].

2.4.2.2 Energy Optimization for Train Operation

For the train operation side, this section only considers two aspects: train trajectory optimization and timetable optimization. Both aspects can impact not only the capacity, customer experience and safety of the rail network, but also the energy consumption. The energy consumption of the railway vehicle is determined by multiple factors, such as journey time, train configuration and weight, and track grade. Meanwhile, the regenerative energy can be produced when the vehicles are braking. The amount of regenerative power generated by a train is dependent on several factors such as the type of train, electrical system used, and operating conditions. Factors such as the size and type of traction motors, weight and speed of the train, and track resistance all play a role in determining the amount of energy that can be recovered through regenerative braking. On average, trains can recover up to 30-40% of the energy consumed during braking, though this ratio can vary based on the specific conditions and system efficiency. Optimizing both the train trajectory and timetable offer significant opportunities to enhance energy efficiency from the train operation side.

Optimization of the train trajectory is a trade-off between the energy consumption and journey time, whilst also considering service quality aspects like punctuality and

passenger comfort as the constraints. For example, in [137], the energy-efficient driving strategies integrating the off-line approximate dynamic programming (ADP) and on-line search process are designed to control the trains such that they will arrive on time regardless of uncertain factors. In [138], a deep deterministic policy gradient (DDPG) based train trajectory optimization approach is proposed. In [139], a mixed integer linear programming based trajectory optimization approach is proposed to reduce traction energy consumption with considering the riding comfort. In Chapter 5, a more comprehensive literature review for train trajectory optimisation will be done.

Additionally, the integrated on-board ESS provides extra potentials to improve the energy efficiency, since more regenerative energy can be collected onboard and more flexible energy flow can be regulated. In [140], a mixed-integer linear programming (MILP) model to address the optimal sizing problem of onboard energy storage devices (OESDs) and minimize the energy consumption for practical train operations was proposed, achieving up to 23.7% energy reduction. In [141], an optimal driving strategy of electric trains with OESDs to minimize the net energy consumption was developed, where the OESDs investment and dynamic power limit are fully considered.

Besides the single train trajectory optimization, the optimization of the timetable offers another angle for improving the energy efficiency from the train operation side. Train timetable optimization refers to the process of adjusting the schedule of trains to achieve a more efficient use of resources, such as energy, personnel, and track infrastructure. Optimizing train schedules can help reduce energy consumption by reducing the amount of time trains spend idle, reducing the frequency of stops, and reducing the amount of energy needed to maintain the train's momentum. Furthermore, the timetable optimization provide opportunities to capture more regenerative energy from the same traction section. Most research optimizes the timetable with the train trajectory taken into consideration. For example, in [142], a joint two-step optimization approach for the train trajectory, timetable, and energy management strategy of the onboard energy storage device to minimize the net energy consumption is proposed, achieving a up to 23.8% energy consumption reduction. Also in [143], an integrated model to optimize

the integrated timetable, which includes both the timetable and the train trajectory to achieve the minimum electrical energy consumption was developed. In [144], a novel approach for energy-efficient timetabling by adjusting the running time allocation of given timetables using train trajectory optimization was proposed to improve the energy efficiency of a timetable.

2.5 Summary

This section has performed a comprehensive review of the railway power supply systems and train traction systems. For the railway power supply systems, in Section 2.2, both traditional transformer-based and power electronic-based power supply systems are introduced. The various configurations to integrate the DERs and ESSs into the railway power supply systems are reviewed. Meanwhile, the benefits and limitations of each configuration are discussed. Furthermore, the future smarter railway power supply systems potentially configured with multiple DERs and ESSs integration have also been envisioned. In Section 2.3, for the train traction system, the current propulsion systems including concentrated and distributed traction systems are reviewed respectively. Moreover, the future trend of advanced techniques in train traction systems has also been discussed. Finally, in Section 2.4, some optimization techniques and their related applications in the railway traction power supply systems have been broadly reviewed.

OPTIMAL COMPENSATION CONTROL OF RAILWAY CO-PHASE TRACTION POWER SUPPLY INTEGRATED WITH RENEWABLE ENERGY BASED ON NSGA-II

In railway traction power supply, the co-phase system with power flow controller (PFC) is capable of tackling power quality issues caused by single-phase traction loads. To reduce the carbon emission, it is proposed to integrate renewable energy with the railway power supply, leading to a more complex system to model, design and control. This chapter first investigates the modelling aspect of this system. To reduce the operating capacity of PFC while addressing the power imbalance, optimal design of the compensation scheme for co-phase system is formulated as a multi-objective optimization problem which is solved by the nondominated sorting genetic algorithm-II (NSGA-II). Furthermore, to eliminate the effect of errors arising from imperfect predictions of the loads and renewable power, a hybrid optimal compensation control is proposed, yielding full and optimal compensations. Comprehensive simulation studies, considering three operation modes that cover variable traction loads, renewable power, as well as braking regenerative power, are conducted. The simulation results confirm the validity of the proposed optimal compensation scheme, achieving an average of more than 20% reduction of operating capacity for the PFC

compared to the full compensation scheme. Meanwhile, the power quality requirement is always satisfied, even in the presence of real-time prediction errors.

3.1 Introduction

The rapid development of railway system is significantly increasing the capacity of rail transport worldwide, further facilitating the shift towards electrification and reduction of carbon emissions. The single-phase 50 Hz/ 25 kV AC power system has been widely applied in electrified traction systems [79]. Generally, in the feeder stations, a step-down transformer is connected between the three-phase power grid and two single-phase catenary overhead lines. Each single-phase provides power for one traction power supply arm, and an insulator is needed between adjacent power supply arms to prevent phase mixture. However, as the traction loads are dynamic, time-varying and distributed in different power supply arms, power imbalance caused by the negative sequence and harmonics in the line current and voltage usually exists [145–147]. Furthermore, there is a limit for the reactive power injected from the traction loads into the three-phase utility grid due to the power factor requirement imposed by the grid code.

To solve the power quality issues, various power compensation solutions have been proposed, though only few of them have been adopted in practice due to the high cost and complexity. The static synchronous compensator (STATCOM) is among the few compensation solutions that have been widely deployed at the three-phase side of the feeder stations [48]. However the reactive power and negative sequence current can still pass through the traction transformer, increasing the risks to the transformers. In [59], a novel co-phase traction power supply system was proposed, where the transformer configuration is still preserved but the insulator is removed. An active power compensator (APC) based on the back-to-back converter is applied and the full compensation control method is demonstrated. The negative sequence current is cancelled and the reactive power is fully compensated, thus achieving the system balance and unity power factor in the grid side. In [148], a new topology for co-phase railway system was also proposed.

A 10 MVA-rated co-phase system has been operated in China and the compensation performance has been validated [62]. But under this full compensation scheme, the APC provides half of the active power and full reactive power of the traction loads, which leads to a high operating capacity requirement. The current conduction power efficiency of converters is about 98% [149–151], therefore a large amount of power loss is incurred due to the high operating capacity. To reduce the capacity while simultaneously improving the power quality is an important research topic. In [60], a partial compensation scheme is presented and the PFC is adopted in the co-phase system. The design, parameter selection and control method are introduced in [66, 68, 152, 153]. In partial compensation, the PFC only compensates part of the negative sequence current and reactive power to reduce the operating capacity. However, the fixed partial compensation strategy is not suitable for all traction loads. A partial compensation scheme adopted for a lower traction load may be inadequate for a higher load case. Hence it is vital to design optimal compensation solutions under different traction load conditions. These raise the needs to achieve the maximum reduction in required system operation capacity while meeting the requirements for system balance and reactive power.

As the railway electrification has had profound societal impacts, the energy landscape has also significantly shifted with the significant penetration of renewable generation [154–158]. The optimal operation of electric railways integrated with renewable energy has gradually drawn more attention, though such an integration inevitably increases the complexity of the system [159]. This chapter investigates the integration scheme as illustrated in Figure 3.1, where the renewable generation provides active power via the DC-link of the back-to-back converter. The batteries can smooth the variations in the power flow. The renewable generators work together with the utility grid to provide the necessary traction power. Here it is assumed that the renewable energy is first absorbed by the batteries, then the excessive renewable energy is fed into the DC link. Thus in this Chapter, the aggregated system combined by the renewable generators and batteries is regarded as a passive power source, which only outputs power but not absorbs power.

To reduce the operating capacity of the PFC as well as the power system imbalance,

CHAPTER 3. OPTIMAL COMPENSATION CONTROL OF RAILWAY CO-PHASE TRACTION POWER SUPPLY INTEGRATED WITH RENEWABLE ENERGY BASED ON NSGA-II

this chapter proposes to formulate the compensation design as a multi-objective optimization problem which is then solved by the NSGA-II. The NSGA-II is a powerful multi-objective optimization method that has been successfully applied to many engineering problems, such as design of the induction machines [160], control of wind turbines [161], and reduction of the fuel consumption and operating costs of hybrid vehicles [162].

The remainder of the chapter is organized as follows. Section 3.2 discusses the modelling of the co-phase system with renewable energy integration. While Section 3.3 presents the principles of full compensation. To identify the optimal compensation schemes under varying traction loads and renewable generations, the NSGA-II is applied. In Section 3.4, to achieve optimal compensation while mitigating the negative impacts of real-time prediction errors in the traction loads and the renewable power, a hybrid optimal compensation control is proposed. In Section 3.5, the effectiveness of the NSGA-II optimization and the optimal control of the hybrid compensation are verified through numerical simulations. The results confirm that the optimal compensation can reduce the operating capacity of the PFC as well as the power loss, while the power quality requirements defined in Section 3.3.2 are always met. Finally, Section 3.6 concludes Chapter 3.

3.2 Modelling of Co-phase System with Renewable Energy Integration

As illustrated in Figure 3.1, the three-phase power supply from the utility grid is split into two single-phase channels by the V/V transformer, a widely adopted transformer configuration in railway power supply system. One single phase ac connects to the traction line directly to feed traction loads. The back-to-back PFC is connected between phase bc and phase ac , which can achieve flexible power compensation and harmonic suppression. The PFC is composed of two voltage source converters and a capacitor in middle to stabilize the DC voltage. In a renewable energy integrated co-phase system, renewable power is injected into the DC link through DC/DC or AC/DC converters. The

3.2. MODELLING OF CO-PHASE SYSTEM WITH RENEWABLE ENERGY INTEGRATION

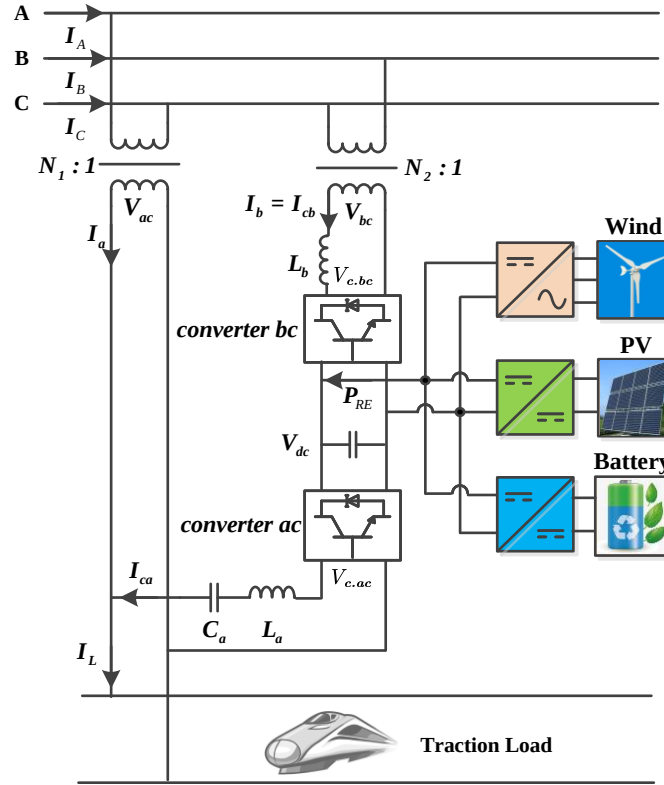


Figure 3.1: Co-phase system with renewable energy integration

detailed models and analysis are introduced below.

3.2.1 Conventional Co-phase System

For the conventional co-phase system without renewable energy, the phasor diagram is shown in Figure 3.2 (a). The analysis is under the fundamental frequency 50 Hz. The three-phase voltages are denoted as $\tilde{V}_A$, $\tilde{V}_B$ and $\tilde{V}_C$. The secondary side voltages are $\tilde{V}_{ac}$ and $\tilde{V}_{bc}$ respectively. The voltage phasors are given in (3.1).

$$\begin{bmatrix} \tilde{V}_A \\ \tilde{V}_B \\ \tilde{V}_C \\ \tilde{V}_{ac} \\ \tilde{V}_{bc} \end{bmatrix} = \begin{bmatrix} V_A e^{j0} \\ V_B e^{-j\frac{2\pi}{3}} \\ V_C e^{j\frac{2\pi}{3}} \\ V_{ac} e^{-j\frac{\pi}{6}} \\ V_{bc} e^{-j\frac{\pi}{2}} \end{bmatrix} \quad (3.1)$$

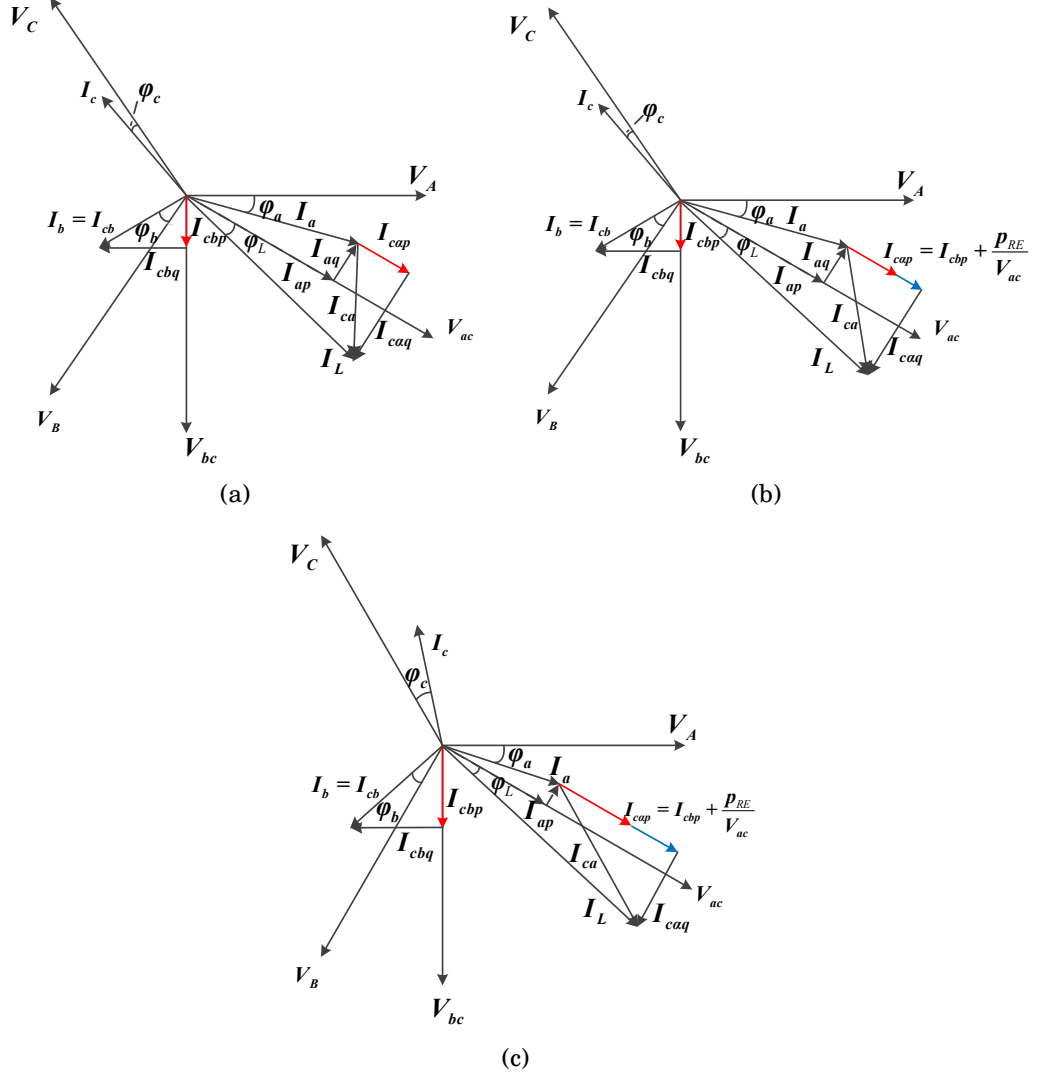


Figure 3.2: Phasor diagrams of co-phase system. (a) Conventional co-phase system. (b) Co-phase system with renewable energy integration. (c) Co-phase system under full compensation.

$\tilde{I}_a$ and $\tilde{I}_b$ are secondary side currents and define $\tilde{I}_c = -\tilde{I}_a - \tilde{I}_b$. φ_a , φ_b and φ_c denote the phase angles at the grid side. The phase angle is positive if the phase voltage leads the current. The currents are given in (3.2).

$$\begin{bmatrix} \tilde{I}_a \\ \tilde{I}_b \\ \tilde{I}_c \end{bmatrix} = \begin{bmatrix} I_a e^{-j\varphi_a} \\ I_b e^{-j(\varphi_b + \frac{2\pi}{3})} \\ -\tilde{I}_a - \tilde{I}_b \end{bmatrix} \quad (3.2)$$

Since the traction loads are fed by phase ac and phase bc together, the traction power including active power P_L and reactive power Q_L can be expressed as (3.3).

$$\begin{aligned} \begin{bmatrix} P_L \\ Q_L \end{bmatrix} &= \begin{bmatrix} V_{ac} I_L \cos \varphi_L \\ V_{ac} I_L \sin \varphi_L \end{bmatrix} = \begin{bmatrix} V_{ac} (I_{ap} + I_{cap}) \\ V_{ac} (I_{aq} + I_{caq}) \end{bmatrix} \\ &= \begin{bmatrix} V_{ac} I_{ap} + V_{bc} I_{cbp} \\ V_{ac} I_{aq} + V_{ac} I_{caq} \end{bmatrix} = \begin{bmatrix} V_{ac} (I_{ap} + \frac{N_1}{N_2} I_{cbp}) \\ V_{ac} (I_{aq} + I_{caq}) \end{bmatrix} \end{aligned} \quad (3.3)$$

where $\cos \varphi_L$ is the load power factor. I_L is the traction load current. N_1 and N_2 are the transformer ratios. I_{ap} , I_{cap} and I_{cbp} are active currents. I_{aq} , I_{caq} and I_{cbq} are reactive currents. According to (3.3), the following can be easily derived

$$\begin{cases} I_{ap} = I_L \cos \varphi_L - \frac{N_1}{N_2} I_{cbp} \\ I_{cap} = \frac{N_1}{N_2} I_{cbp} \end{cases} \quad (3.4)$$

Further, based on Figure 3.2 (a), the reactive currents are given as

$$\begin{cases} I_{aq} = \tan(\frac{\pi}{6} - \varphi_a)(I_L \cos \varphi_L - \frac{N_1}{N_2} I_{cbp}) \\ I_{caq} = I_L \sin \varphi_L + \tan(\frac{\pi}{6} - \varphi_a)(I_L \cos \varphi_L - \frac{N_1}{N_2} I_{cbp}) \\ I_{cbq} = \tan(\frac{\pi}{6} + \varphi_b) I_{cbp} \end{cases} \quad (3.5)$$

Combining (3.4) and (3.5) yields

$$\begin{bmatrix} I_{ap} \\ I_{aq} \\ I_{cap} \\ I_{caq} \\ I_{cbp} \\ I_{cbq} \end{bmatrix} = \begin{bmatrix} I_L \cos \varphi_L - \frac{N_1}{N_2} I_{cbp} \\ \tan(\frac{\pi}{6} - \varphi_a)(I_L \cos \varphi_L - \frac{N_1}{N_2} I_{cbp}) \\ \frac{N_1}{N_2} I_{cbp} \\ I_L \sin \varphi_L + \tan(\frac{\pi}{6} - \varphi_a)(I_L \cos \varphi_L - \frac{N_1}{N_2} I_{cbp}) \\ I_{cbp} \\ \tan(\frac{\pi}{6} + \varphi_b) I_{cbp} \end{bmatrix} \quad (3.6)$$

3.2.2 Co-phase System with Renewable Energy Integration

When the renewable energy is integrated into the co-phase system, three main operation modes are considered below. It should be noted that, based on the assumption in this

CHAPTER 3. OPTIMAL COMPENSATION CONTROL OF RAILWAY CO-PHASE TRACTION POWER SUPPLY INTEGRATED WITH RENEWABLE ENERGY BASED ON NSGA-II

Chapter, from the point of view from the DC link, the aggregated system of renewable energy resources and battery systems is regarded as a passive power source, which is considered to only outputs power but not absorbs power.

- Mode 1: When the traction load is positive and the traction power requirement S_L is greater than the renewable power P_{RE} , the traction power is supplied by both the utility grid and the renewable generation.
- Mode 2: When the traction load is positive and the traction power requirement S_L is less than renewable power P_{RE} , the traction power requirement is met by renewable energy. The excessive renewable power is fed into the power grid.
- Mode 3: When the traction power is negative, i.e. the train is operated in the regeneration mode. The regenerative power from trains and renewable power are all fed to the power grid.

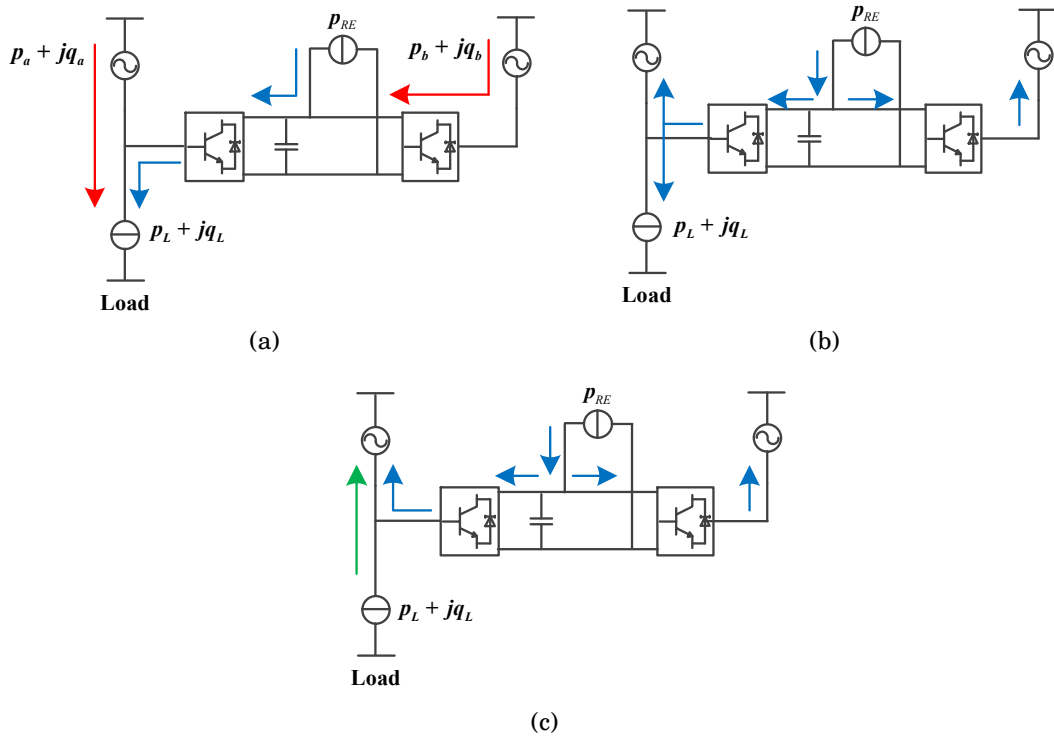


Figure 3.3: Power flow diagrams. (a) Operation mode 1. (b) Operation mode 2. (c) Operation mode 3.

3.2. MODELLING OF CO-PHASE SYSTEM WITH RENEWABLE ENERGY INTEGRATION

The power flow of the three operation modes are shown in Figure 3.3. Due to the renewable energy integration, the phasor diagram is revised accordingly as shown in Figure 3.2 (b). Figure 3.2 (b) is a generalized phasor diagram. Even though the magnitude and direction of the phasors are variable in this diagram, the phasor relations remain the same. Thus the analysis below is applicable to all the three operation modes. Take the power flow direction in Figure 3.3 (a) as the reference direction and based on the power balance principle, (3.7) can be obtained, where P_{RE} represents the renewable power.

$$\begin{aligned}
 P_L &= P_a + P_{ca} = P_a + P_{cb} + P_{RE} \\
 &= V_{ac}(I_{ap} + I_{cap}) = V_{ac}I_{ap} + V_{bc}I_{cbp} + P_{RE} \\
 &= V_{ac}(I_{ap} + \frac{N_1}{N_2}I_{cbp} + \frac{P_{RE}}{V_{ac}}) \\
 &= V_{ac}I_L \cos \varphi_L
 \end{aligned} \tag{3.7}$$

According to (3.7), (3.6) can be revised to (3.8). In order to simplify the analysis, it is assumed that the transformer ratio $N_1 = N_2$. In Figure 3.2 (b), the phase angle φ_c satisfies (3.9).

$$\begin{bmatrix} I_{ap} \\ I_{aq} \\ I_{cap} \\ I_{caq} \\ I_{cbp} \\ I_{cbq} \end{bmatrix} = \begin{bmatrix} I_L \cos \varphi_L - \frac{N_1}{N_2}I_{cbp} - \frac{P_{RE}}{V_{ac}} \\ \tan(\frac{\pi}{6} - \varphi_a)(I_L \cos \varphi_L - \frac{N_1}{N_2}I_{cbp} - \frac{P_{RE}}{V_{ac}}) \\ \frac{N_1}{N_2}I_{cbp} + \frac{P_{RE}}{V_{ac}} \\ I_L \sin \varphi_L + \tan(\frac{\pi}{6} - \varphi_a)(I_L \cos \varphi_L - \frac{N_1}{N_2}I_{cbp} - \frac{P_{RE}}{V_{ac}}) \\ I_{cbp} \\ \tan(\frac{\pi}{6} + \varphi_b)I_{cbp} \end{bmatrix} \tag{3.8}$$

$$\begin{aligned}
 \tan \varphi_c &= \frac{\sin \varphi_c}{\cos \varphi_c} = \frac{I_{cq}}{I_{cp}} \\
 &= \frac{-I_a \sin(\frac{\pi}{3} - \varphi_a) + I_b \sin(\frac{\pi}{3} + \varphi_b)}{I_a \cos(\frac{\pi}{3} - \varphi_a) + I_b \cos(\frac{\pi}{3} + \varphi_b)} \\
 &= \frac{-\frac{I_{ap}}{\cos(\frac{\pi}{6} - \varphi_a)} \sin(\frac{\pi}{3} - \varphi_a) + \frac{I_{cbp}}{\cos(\frac{\pi}{6} + \varphi_b)} \sin(\frac{\pi}{3} + \varphi_b)}{\frac{I_{ap}}{\cos(\frac{\pi}{6} - \varphi_a)} \cos(\frac{\pi}{3} - \varphi_a) + \frac{I_{cbp}}{\cos(\frac{\pi}{6} + \varphi_b)} \cos(\frac{\pi}{3} + \varphi_b)}
 \end{aligned} \tag{3.9}$$

Substituting (3.8) into (3.9), the relationships between I_{cbp} and φ_a , φ_b and φ_c can be derived as (3.10), where K is the compensation factor determined by φ_a , φ_b and φ_c . Based on (3.8) and (3.10), the converter compensation currents can be calculated as (3.11).

$$\begin{aligned}
 I_{cbp} &= y(\varphi_a, \varphi_b, \varphi_c) \\
 &= \frac{(\cos(\frac{5\pi}{6} - \varphi_b)(\sin \varphi_c \sin(\frac{\pi}{6} + \varphi_a) + \cos \varphi_c \cos(\frac{\pi}{6} + \varphi_a)))(I_L \cos \varphi_L - \frac{P_{RE}}{V_{ac}})}{\begin{pmatrix} \sin \varphi_c (\cos(\frac{\pi}{6} - \varphi_a) \cos(\frac{\pi}{3} + \varphi_b) + \sin(\frac{\pi}{6} + \varphi_a) \cos(\frac{5\pi}{6} - \varphi_b)) - \\ \cos \varphi_c (\cos(\frac{\pi}{6} - \varphi_a) \sin(\frac{\pi}{3} + \varphi_b) - \cos(\frac{\pi}{6} + \varphi_a) \cos(\frac{5\pi}{6} - \varphi_b)) \end{pmatrix}} \quad (3.10) \\
 &= K(\varphi_a, \varphi_b, \varphi_c) \cdot (I_L \cos \varphi_L - \frac{P_{RE}}{V_{ac}})
 \end{aligned}$$

$$\begin{bmatrix} I_{cap} \\ I_{caq} \\ I_{cbp} \\ I_{cbq} \end{bmatrix} = \begin{bmatrix} KI_L \cos \varphi_L + (1 - K) \frac{P_{RE}}{V_{ac}} \\ K_a(I_L \cos \varphi_L - \frac{P_{RE}}{V_{ac}}) + I_L \sin \varphi_L \\ K(I_L \cos \varphi_L - \frac{P_{RE}}{V_{ac}}) \\ K_b(I_L \cos \varphi_L - \frac{P_{RE}}{V_{ac}}) \end{bmatrix} \quad (3.11)$$

where

$$\begin{bmatrix} K_a \\ K_b \end{bmatrix} = \begin{bmatrix} \tan(\frac{\pi}{6} - \varphi_a)(1 - K) \\ \tan(\frac{\pi}{6} + \varphi_b)K \end{bmatrix} \quad (3.12)$$

3.3 Analysis of Two Compensation Strategies for Co-phase Systems

3.3.1 Full Compensation Strategy

In the literature, the full compensation strategy is widely applied in the co-phase system. According to [59], this is defined as such that both negative sequence current and reactive power injected to the three-phase power grid are all zeros. In this chapter, in order to take into account of the effect of power factors to the power quality and the converter capacity, the definition of full compensation is slightly modified. Three-phase power

factors are allowed to vary in the range according to the grid code while the negative sequence current is limited to zero. In this modified full compensation scheme, three-phase currents and voltages are still balanced, thus the phasor sum of $\tilde{I}_a + \tilde{I}_b + \tilde{I}_c = 0$, and $I_a = I_b = I_c$. However a certain amount of reactive power can be injected into the power grid. Accordingly, under the slightly modified full compensation strategy, the phase angles can be predefined as $\varphi_a = \varphi_b = \varphi_c = \varphi$, (3.9) can thus be revised as (3.13).

$$\tan \varphi = \frac{\sin \varphi}{\cos \varphi} = \frac{-I_a \sin(\frac{\pi}{3} - \varphi) + I_b \sin(\frac{\pi}{3} + \varphi)}{I_a \cos(\frac{\pi}{3} - \varphi) + I_b \cos(\frac{\pi}{3} + \varphi)} \quad (3.13)$$

With these pre-defined phase angles, the full power compensation factor K_{full} can be evaluated using (3.10). The balanced phasor diagram is shown in Figure 3.2 (c).

3.3.2 Optimal Compensation Strategy Based on NSGA-II

Algorithm

In this section, an optimal compensation strategy, instead of the full compensation strategy presented in the aforementioned subsection, is presented based on NSGA-II. The aim is to search for a set of phase angles $\varphi_a, \varphi_b, \varphi_c$, which can lead to reducing the operating capacity of PFC while meeting the power quality requirements, rather than presetting these phase angles in the full compensation strategy. This is a multi-objective optimization problem, which can generally be formulated as follows:

$$\begin{aligned} \min \quad & F = \{f_1(x), \dots, f_m(x)\} \\ \text{s.t.} \quad & h_r(x) = 0 \quad r = 1, \dots, N_r \\ & g_s(x) \leq 0 \quad s = 1, \dots, N_s \\ & x^T = [x_1, \dots, x_I] \\ & x_{imin} \leq x_i \leq x_{imax} \quad i = 1, 2, \dots, I \end{aligned} \quad (3.14)$$

where F is the overall objective function, f_i ($i = 1, \dots, m$) are individual objective functions, h_r and g_s are equality and inequality constraints respectively, x_{imin} and x_{imax} are the

lower and upper limits of decision variables x_i ($i = 1, \dots, I$). In the three-phase power supply system, the approximate calculation of the negative sequence voltage unbalance ratio ε_u is defined in (3.15) based on [163, 164], which is used to evaluate the unbalance of the traction power system. There is a lack of standards for system unbalance within IEEE. Based on the GB/T 15543-2008 Power Quality - Three-phase Voltage Unbalance, a maximum allowable voltage unbalance at point of common coupling (PCC) is 2% for long-term [163, 164]. Thus

$$\varepsilon_u = \frac{\sqrt{3}|I^-|U_L}{S_c} \times 100\% \leq 2\% \quad (3.15)$$

where $|I^-|$ is the negative sequence current of the three-phase power grid, S_c is the short-circuit capacity and U_L is the line-to-line voltage. From (3.15), $|I^-|$ is deduced in (3.16).

$$|I^-| \leq \frac{2\% \cdot S_c}{\sqrt{3}U_L} \quad (3.16)$$

$|I^-|$ can be calculated by (3.17).

$$|I^-| = \frac{1}{3} \cdot \left| \tilde{I}_a + \tilde{I}_b \cdot e^{j\frac{4\pi}{3}} + \tilde{I}_c \cdot e^{j\frac{2\pi}{3}} \right| \quad (3.17)$$

The PFC includes the rectifier part and inverter part. Thus the operating capacity S of PFC is defined as

$$S = U_{ac}I_{ca} + U_{bc}I_{cb} \quad (3.18)$$

Since the traction loads and renewable energy are predictable based on the existing information such as timetable and historic data, they can be taken as known a priori in the optimization. Thus from (3.2), (3.8) and (3.11), the negative sequence current and operating capacity can be expressed as the function of variables φ_a , φ_b and φ_c , i.e. $|I^-| = f_1(\varphi_a, \varphi_b, \varphi_c)$ and $S = f_2(\varphi_a, \varphi_b, \varphi_c)$.

For the co-phase system, the operating capacity S and negative sequence current $|I^-|$ are both expected to be minimized. By choosing suitable phase angles $(\varphi_a, \varphi_b, \varphi_c)$

and controlling compensation currents, it is feasible to achieve optimal compensation control for given traction loads and renewable power injection. Further, the three-phase power factors are supposed to be within the range of 0.95 to 1 according to the grid code, i.e. $-18.19^\circ \leq \varphi_a, \varphi_b, \varphi_c \leq 18.19^\circ$. Taking this power factor range and (3.16) as the constraints, the co-phase system compensation design can be formulated as the following constrained multi-objective optimization problem:

$$\begin{aligned} \min \quad & \begin{cases} |I^-| = f_1(\varphi_a, \varphi_b, \varphi_c) \\ S = f_2(\varphi_a, \varphi_b, \varphi_c) \end{cases} \\ \text{s.t.} \quad & \begin{cases} |I^-| = f_1(\varphi_a, \varphi_b, \varphi_c) \leq \frac{2\% \cdot S}{\sqrt{3}U_L} \\ 0.95 \leq \arccos(\varphi_i) \leq 1 \quad (i = a, b, c) \end{cases} \end{aligned} \quad (3.19)$$

NSGA-II is an improved fast non-dominate sorting strategy based on the genetic algorithm. Compared to the original NSGA, NSGA-II has the following distinctive features [165]:

- In NSGA-II, a crowded comparison approach is used to replace the original sharing function approach in NSGA. Thus, NSGA-II does not require any user-defined parameter for maintaining diversity among population members.
- NSGA-II has a computational complexity of $O(MN^2)$ (where M is the number of objectives and N is the population size). While the overall computational complexity of the original NSGA is $O(MN^3)$.
- The elitism strategy is adopted in NSGA-II, which can speed up convergence of the algorithm significantly and help preventing the loss of good solutions.

Extensive research has already demonstrated the outstanding performance and convergence speed of the NSGA-II in solving a broad range of multi-objective optimization problems. Figure 3.4 shows the flowchart of the NSGA-II. The whole procedure of NSGA-II includes several steps: 1) Initialize parent population of size N ; 2) Produce offspring by genetic operations and merge parent population into a new population of size $2N$;

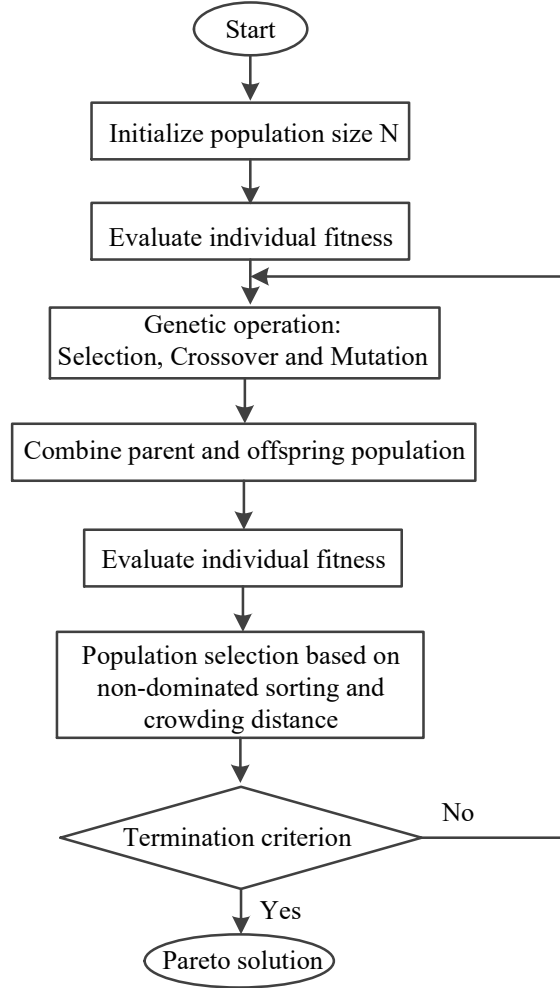


Figure 3.4: Flowchart of NSGA-II algorithm

3) Evaluate the fitness of individual solutions and select N better individuals as a new parent population; 4) Termination criterion judgment.

The goal of the multi-objective optimization is to identify the Pareto front which is also called as Pareto optimal solutions. For the problem in (3.19), NSGA-II will produce the Pareto front from which a set of optimal phase angles $(\varphi_a, \varphi_b, \varphi_c)$ are selected. This optimal set of phase angles is then applied to (3.10), hence the optimal power compensation factor $K_{optimal}$ is calculated. Subsequently the compensation currents I_{ca} and I_{cb} can be calculated based on (3.11) to achieve the optimal compensation. The whole process of the optimal compensation control is shown in Figure 3.5.

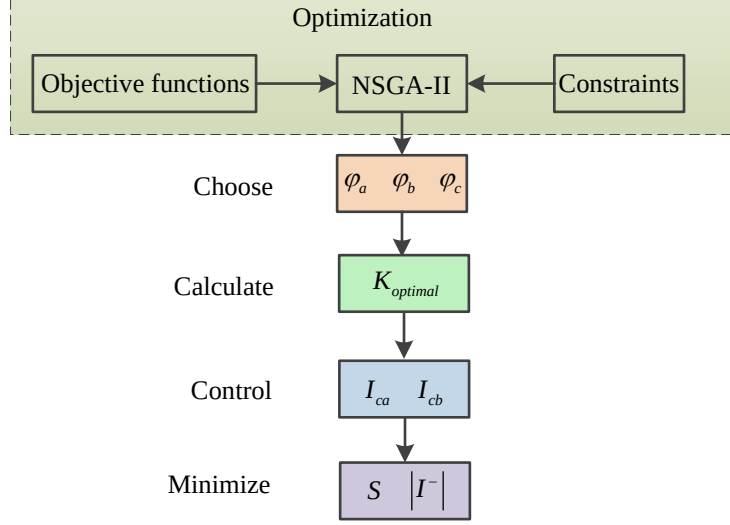


Figure 3.5: Process of optimal control

3.4 A Hybrid Optimal Compensation Control

The previous section presents an optimal operation scheme for the co-phase system based on the assumptions that the traction load and the renewable generation are known a prior based on some prediction models. However, in reality, these prediction models may not be accurate enough. Therefore, to countermeasure the prediction errors in real time applications, this section proposes and presents a hybrid optimal control scheme based on NSGA-II, which combines both the proposed optimal compensation and full compensation. In the proposed hybrid optimal compensation control scheme, the full compensation scheme is used to eliminate the negative sequence current produced due to the prediction error, while the optimal compensation introduced in Section 3.3.2 is deployed to achieve the operating capacity reduction.

3.4.1 Reference Current Calculation

In the hybrid optimal compensation control, a step is to calculate the reference current. This section introduces an effective reference current calculation method based on the instantaneous power analysis approach introduced in [60]. Using this method, based on the required traction power, the real-time reference currents can be calculated for

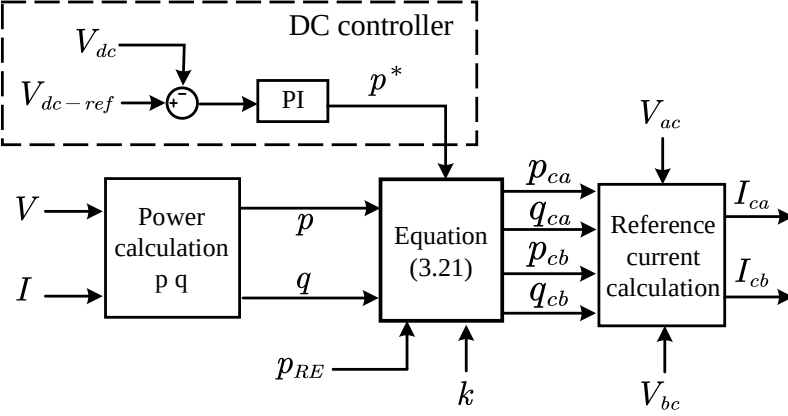


Figure 3.6: Reference current calculation

both the full compensation scheme (using full compensation factor K_{full}) or optimal compensation scheme (using optimal compensation factor $K_{optimal}$). The single-phase traction load instantaneous power is given by (3.20), the derivation of which is detailed in Appendix A.

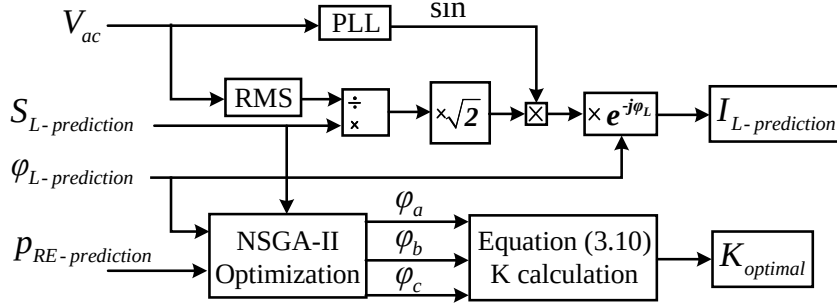
$$\begin{bmatrix} p \\ q \end{bmatrix} = \begin{bmatrix} V_{ac} & V_{ac}e^{-j\frac{\pi}{2}} \\ V_{ac}e^{-j\frac{\pi}{2}} & -V_{ac} \end{bmatrix} \begin{bmatrix} I_L \\ I_L e^{-j\frac{\pi}{2}} \end{bmatrix} \quad (3.20)$$

Based on (3.11), the real-time power of PFC is expressed as (3.21).

$$\begin{bmatrix} p_{ca} \\ q_{ca} \\ p_{cb} \\ q_{cb} \end{bmatrix} = \begin{bmatrix} K(p - P_{RE}) + P_{RE} \\ K_a(p - P_{RE}) + q \\ K(p - P_{RE}) + p^* \\ K_b((p - P_{RE}) + p^*) \end{bmatrix} \quad (3.21)$$

where compensation factor K can either be K_{full} , hence implementing the full compensation. Or, if K is set to $K_{optimal}$, then the optimal compensation is implemented. The inverse transformation of (3.20) is used for reference current calculation, yielding (3.22).

$$\begin{cases} I_{ca}^* = \frac{V_{ac}p_{ca} + V_{ac}e^{-j\frac{\pi}{2}}q_{ca}}{V_{ac}^2 + (V_{ac}e^{-j\frac{\pi}{2}})^2} \\ I_{cb}^* = \frac{V_{bc}p_{cb} + V_{bc}e^{-j\frac{\pi}{2}}q_{cb}}{V_{bc}^2 + (V_{bc}e^{-j\frac{\pi}{2}})^2} \end{cases} \quad (3.22)$$


 Figure 3.7: Real-time current synchronization and $K_{optimal}$ calculation

The control block is shown in Figure 3.6. The PI controller is used to stabilize the DC-link voltage.

3.4.2 Real-time Current Synchronization and Calculation of Optimal Compensation Factor

As illustrated in Section 3.3, the traction load S_L and its power factor angle φ_L can be predicted in advance. Then the real-time current I_L can be predicted using (3.23) and needs to be synchronized for instantaneous power calculation. A phase-locked loop (PLL) is employed to achieve the phase synchronization of voltage V_{ac} . Based on the predicted renewable P_{RE} , the optimal compensation factor $K_{optimal}$ can be also obtained. The control diagram is shown in Figure 3.7, where $I_{L-prediction}$ stands for predicted load current, $S_{L-prediction}$ for predicted traction load, and $\varphi_{L-prediction}$ for predicted power factor angle.

$$I_{L-prediction} = \frac{\sqrt{2}S_{L-prediction}}{V_{ac}} \sin(\omega t - \frac{\pi}{6} - \varphi_L) \quad (3.23)$$

3.4.3 Hybrid Optimal Compensation Control

The NSGA-II based optimal compensation depends on the prediction accuracy of the traction loads and renewable energy. If the prediction error is not considered in the control design, it is highly likely that the negative sequence current will exceed the limit.

Figure 3.8 illustrates the hybrid optimal compensation control scheme, which combines both the optimal compensation scheme and the full compensation branch. The latter is used to estimate and correct the errors in the converter reference currents which are initially determined using the optimal compensation scheme and based on the predicted traction and renewable powers. The whole procedure is summarized as follows: 1) Compare the real-time measured renewable power P_{RE} and traction current I_L and their corresponding predicted values, then calculate the current and power differences, ΔI_L and ΔP_{RE} respectively. 2) Based on ΔI_L and measured voltage V_{ac} , calculate instantaneous error power Δp_L and Δq_L according to (3.20). 3) As stated in Section 3.3.1, for the traditional full compensation scheme, the three phase angles are set as $\varphi_a = \varphi_b = \varphi_c = 0^\circ$. Hence based on (3.10), the full compensation factor K_{full} can be calculated as 0.5. 4) Substituting K_{full} and ΔP_{RE} to (3.21), the required additional compensation powers for the PFC, Δp_{ca} , Δq_{ca} and Δp_{cb} , Δq_{cb} can be calculated. 5) These quantities are substituted in (3.22) to calculate the additional current ΔI_{ca} and ΔI_{cb} . 6) Finally the reference compensation currents can be obtained as

$$\begin{bmatrix} I_{ca}^* \\ I_{cb}^* \end{bmatrix} = \begin{bmatrix} I_{ca-prediction} + \Delta I_{ca} \\ I_{cb-prediction} + \Delta I_{cb} \end{bmatrix} \quad (3.24)$$

Note both $I_{ca-prediction}$ and $I_{cb-prediction}$ are calculated from the optimal compensation control, described in Section 3.3.2. $K_{optimal}$ is the optimal power compensation factor, calculated from (3.10), using the optimal set of $(\varphi_a, \varphi_b, \varphi_c)$ optimized by NSGA-II. With this hybrid compensation scheme, no extra negative sequence current will be produced and the power quality of the three-phase power grid can always meet the requirements in the presence of prediction errors of the traction load and renewable power.

3.5 Simulation Studies

In order to verify the effectiveness of the proposed NSGA-II based optimal compensation and the control performance, a number of simulation experiments were conducted using Matlab/Simulink. The simulation schematic circuit is shown in Figure 3.9. The traction

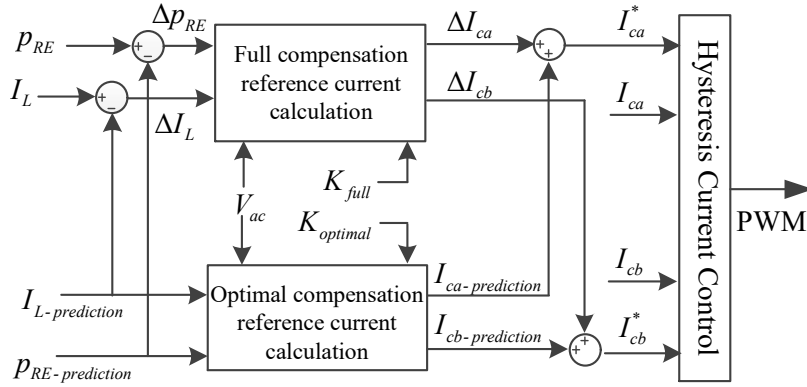


Figure 3.8: Hybrid optimal compensation control

loads and renewable energy are simulated as controllable current sources. The system parameters are listed in Table 3.1. To reduce the operation voltage of converter ac, instead of only adopting a inductor L_a , a series capacitor C_a is also added and the coupled impedance combined by C_a and L_a becomes capacitive from inductive. In this case, an opposite voltage with V_{ac} is formed as additional voltage support when inductive reactive compensation current passes through the capacitive-coupled impedance. There can be conditions under which the value of $V_{c.ac}$ can be lower than that of V_{ac} .

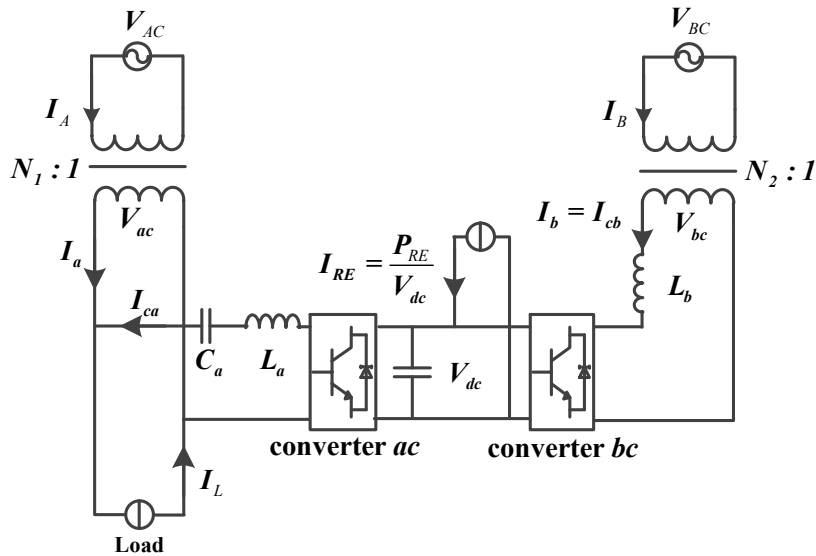


Figure 3.9: Simulation schematic circuit

Table 3.1: System Simulation Parameters

Items	Description
Three-phase line-to-line voltage V_{AC}, V_{BC}	190 kV
Short circuit capacity S_c	500 MVA
V/V transformer	60 MVA 190 kV/ 27.5 kV
PFC DC capacitor	10000 μF
PFC DC voltage	65 kV
Phase ac coupling capacitance C_a	44.5 μF
Phase ac coupling inductance L_a	50 mH
Phase bc coupling inductance L_b	30 mH

3.5.1 Comparison between Full Compensation and Optimal Compensation without Renewable Energy

In this section, the validity of NSGA-II based optimization is first verified without renewable energy. To emulate the characteristic of time-varying train loads and different operation modes including traction and regeneration, the load power factor is set to 0.95. The traction loads are arranged as follows:

- 0~0.3s $S_L = 0$
- 0.3 s~0.55 s $S_L=30$ MVA

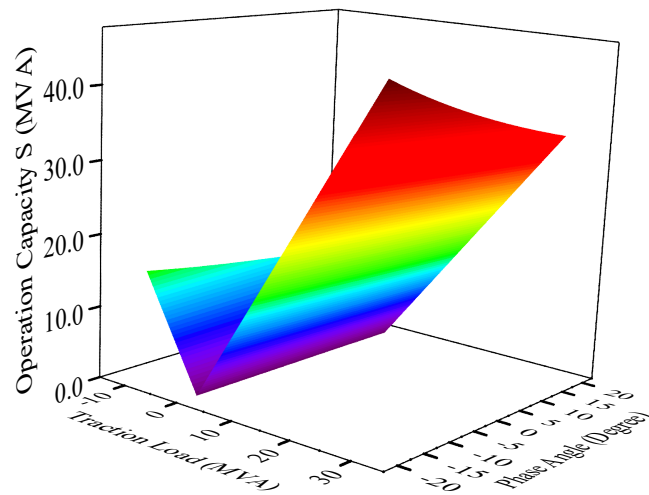


Figure 3.10: Operating capacity comparison under full compensation with different phase angles

- 0.55 s~0.8 s $S_L=15$ MVA
- 0.8 s~1.05 s $S_L=4$ MVA
- 1.05 s~1.3 s $S_L=-10$ MVA
- 1.3 s~1.4 s $S_L=0$

For full compensation, as discussed in Section 3.3.1, $\varphi_a = \varphi_b = \varphi_c$ is required. The comparison of operating capacity with different phase angles is analyzed, as shown in Figure 3.10. It is evident that, compared to the full compensation where $\varphi_a = \varphi_b = \varphi_c = 0$, the operating capacity is reduced for larger phase angles. That is due to the fact that the PFC only provides part of the reactive power rather in full.

In the simulation, the total population of NSGA-II is set to 200 and iteration steps are 300. The crossover probability is 0.9 and the mutation probability is 0.2. By utilizing the NSGA-II algorithm for optimization, the Pareto optimal solutions are obtained as illustrated in Figure 3.11. It is shown that the voltage imbalance of the power grid is below the limit 2% for all traction loads. The solutions with the smallest operating

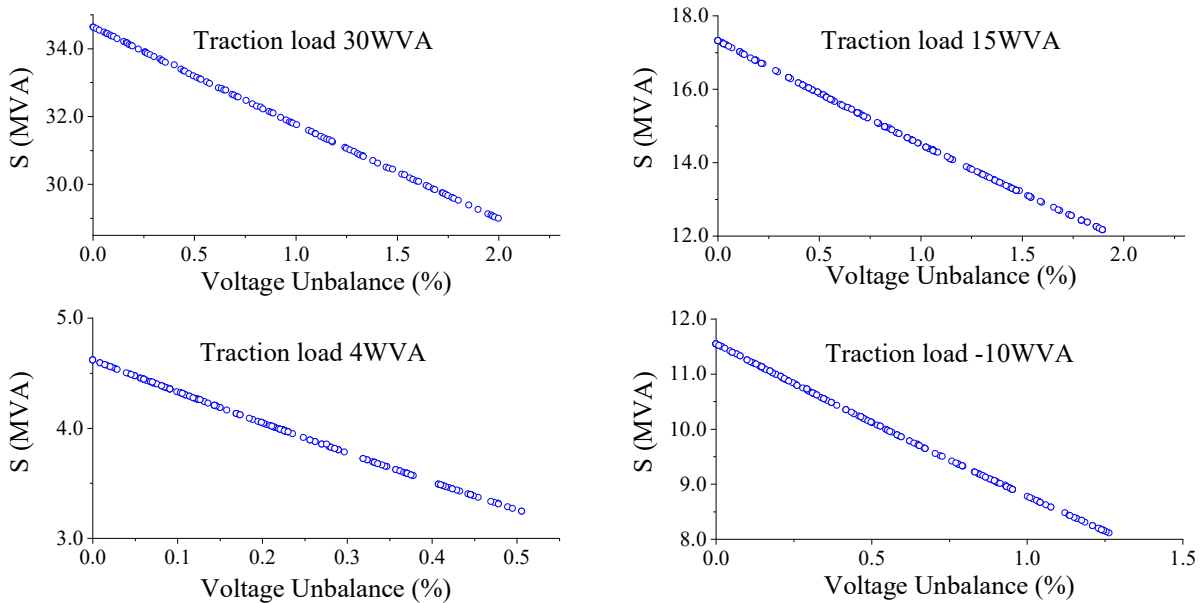


Figure 3.11: Pareto optimal solutions for varying traction loads without renewable energy integration

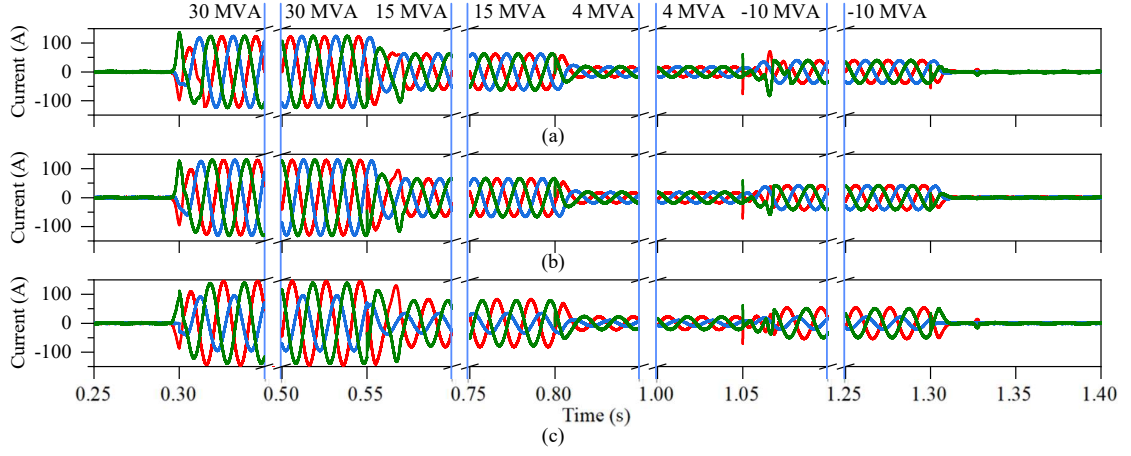


Figure 3.12: Three-phase currents without renewable energy integration. (a) Full compensation $\varphi = 0^\circ$. (b) Full compensation $\varphi = 18.19^\circ$. (c) Optimal compensation.

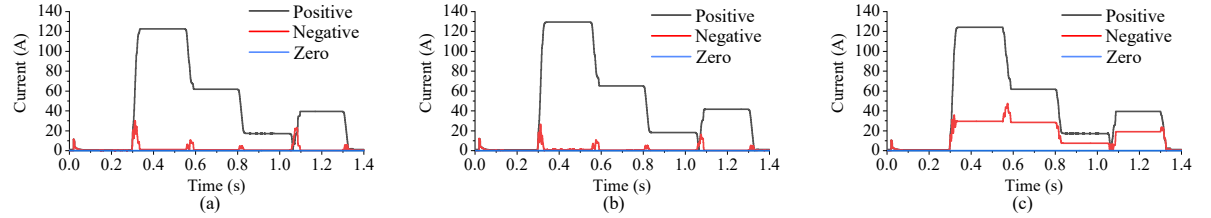


Figure 3.13: Positive, negative and zero sequence currents without renewable integration (a) Full compensation $\varphi = 0^\circ$. (b) Full compensation $\varphi = 18.19^\circ$. (c) Optimal compensation.

capacity S are selected (see Table 3.2). In this way, the optimal operating capacity compensation is achieved.

The three-phase currents shown in Figure 3.12 (a)-(c) corresponding to the full and optimal compensation schemes are the grid side currents I_A , I_B and I_C in Figure 3.1. The stable-state currents are ignored here. For full compensation, two cases with $\varphi = 0^\circ$ and $\varphi = 18.19^\circ$ are adopted. In Figure 3.13 (a), (b) and (c), the black, red and blue lines represent positive sequence, negative sequence and zero sequence currents respectively. According to (3.16) and the parameters listed in Table 3.1, the limit of negative sequence current is calculated to be 30.4 A. Under full compensation, the negative sequence currents are almost zero and three-phase currents are balanced for all traction loads, which are illustrated in Figure 3.12 (a)-(b) and Figure 3.13 (a)-(b). Under optimal compensation, the three-phase currents in Figure 3.12 (c) are unbalanced but

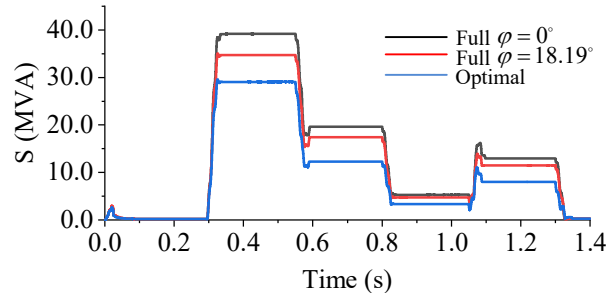


Figure 3.14: Comparison of operating capacity without renewable energy integration

the negative sequence currents for all traction loads are below the limit except for the allowed transient overshoot (see Figure 3.13 (c)). The results meet the control expectation.

The operating capacity comparison of PFC is shown in Figure 3.14. The black line and red line correspond to the full compensation strategy with $\varphi = 0^\circ$ and $\varphi = 18.19^\circ$ respectively. Under full compensation, when $\varphi = 0^\circ$, the reactive power provided by the three-phase power grid is zero. However, choosing the phase angle $\varphi = 18.19^\circ$ leads to the operating capacity reduction, which is consistent with previous results. The blue line represents the optimal operating capacity compensation. It can be seen, compared to full compensation with $\varphi = 0^\circ$, that the operating capacity of PFC is reduced for all traction loads after optimization. The operating capacity reduction ratio for varying traction loads is 25.8%, 35.9%, 35.8% and 38.0% respectively, with an average of 33.9%. The maximum capacity reduction reaches 10.1 MVA.

3.5.2 Comparison between Full Compensation and Optimal Compensation with Renewable Energy Integration

In the simulation, the renewable power of 6.5MW and 1MW are applied at 0.3s. Since renewable energy varies slowly compared to the traction loads in reality, the renewable energy is simulated as a constant current source which only provides active power. The traction loads are the same as Section 3.5.1. After 1.3s, the traction load is zero and the renewable is fed to the power grid. The three operation modes discussed in Section 3.2.2 are all included in simulation.

After optimization by NSGA-II, the Pareto solutions for renewable energy 6.5 MW

CHAPTER 3. OPTIMAL COMPENSATION CONTROL OF RAILWAY CO-PHASE TRACTION POWER SUPPLY INTEGRATED WITH RENEWABLE ENERGY BASED ON NSGA-II

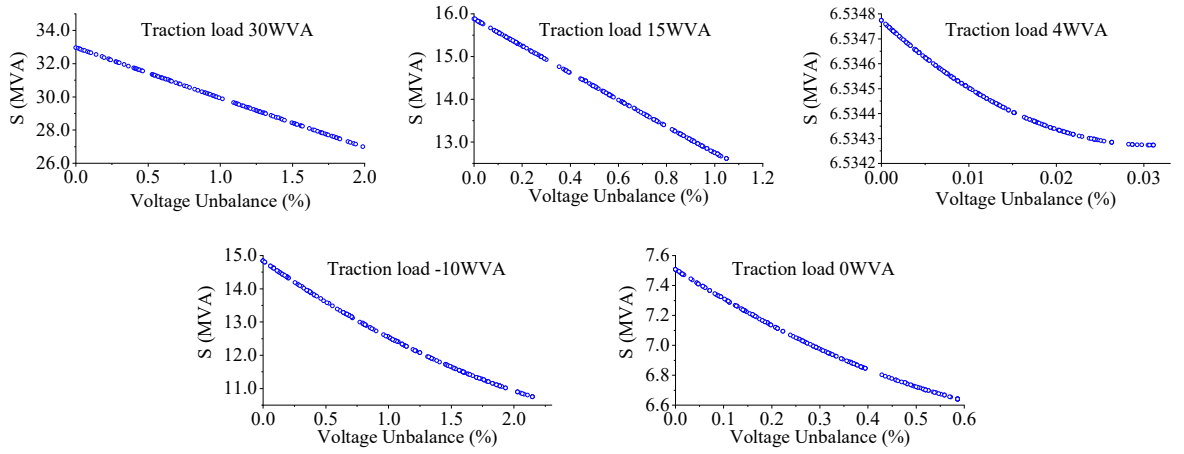


Figure 3.15: Pareto optimal solutions for varying traction load with renewable 6.5MW

are acquired and shown in Figure 3.15. The optimal phase angles are listed in Table 3.2. The three-phase grid side currents are shown in Figure 3.16 (a)-(d) including full and optimal compensation with renewable generations 6.5 MW and 1 MW. Note that the transient period shown in Figure 3.12 and Figure 3.16 is due to the sudden change of operation mode. The PI controller used for the DC-link voltage and current control, also with large filter inductors, slow the response speed. The negative sequence currents shown in Figure 3.17 and Figure 3.18 are below the limit under either full or optimal compensation.

For both cases with two renewable power 6.5 MW and 1 MW, the comparison results of both full compensation and optimal compensation are shown in Figure 3.19 (a) and (b). With renewable energy integration, the optimal compensation strategy based on NSGA-II still shows its effectiveness in operating capacity reduction. Compared to full compensation with $\varphi = 0^\circ$, when renewable energy is 6.5WM, the operating capacity reduction is 25.3%, 25.3%, 3.2%, 37.1% and 13.7%, with an average 20.9%. The maximum reduction in capacity is 9.2 MVA. When renewable energy is 1 WM, the capacity reduction are 25.6%, 35.9%, 20.4%, 39.6% and 22.2%. The average reduction ratio is 28.7% and the maximum reduction in capacity is 9.9 MVA. According to Figure 3.14 and Figure 3.19, it is evident that when renewable energy is integrated, the operating capacity will not increase significantly and can even be reduced under the optimal compensation scheme.

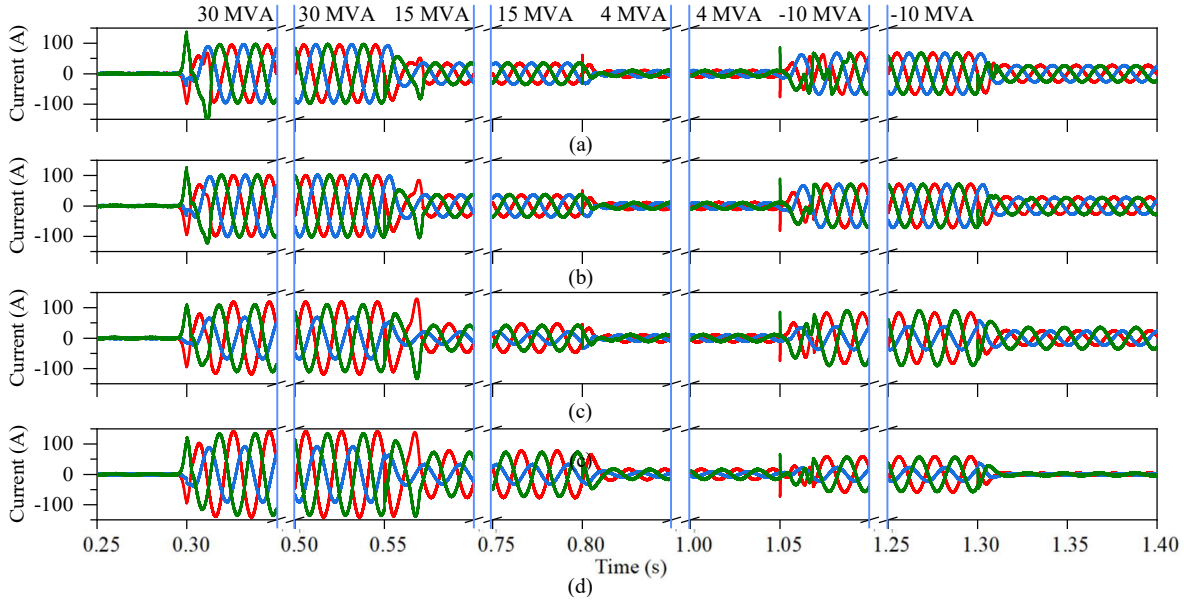


Figure 3.16: Three-phase currents with renewable energy integration. (a) Full compensation $\varphi = 0^\circ$ with renewable 6.5MW. (b) Full compensation $\varphi = 18.19^\circ$ with renewable 6.5WM. (c) Optimal compensation with renewable 6.5MW. (d) Optimal compensation with renewable 1MW.

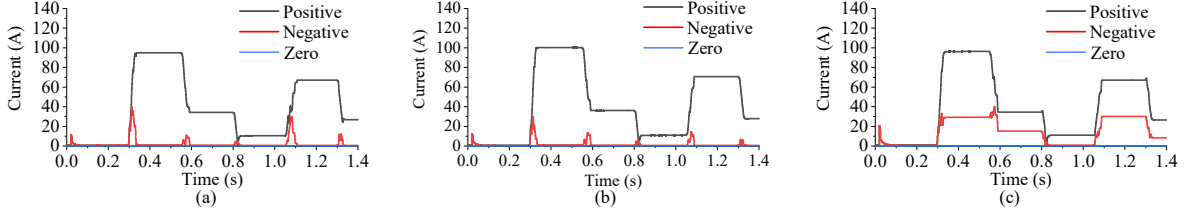


Figure 3.17: Positive, negative and zero sequence currents (Renewable 6.5MW) (a) Full compensation $\varphi = 0^\circ$. (b) Full compensation $\varphi = 18.19^\circ$. (c) Optimal compensation.

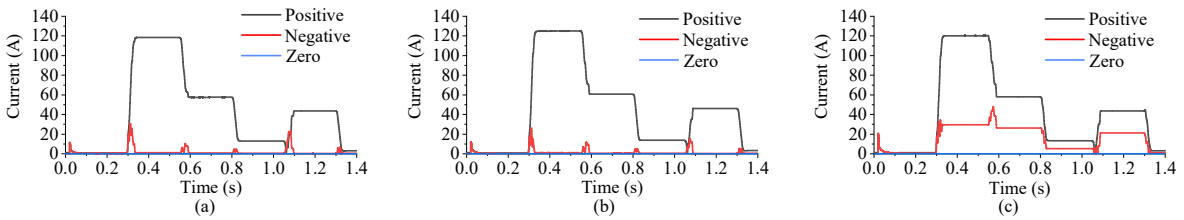


Figure 3.18: Positive, negative and zero sequence currents (Renewable 1MW) (a) Full compensation $\varphi = 0^\circ$. (b) Full compensation $\varphi = 18.19^\circ$. (c) Optimal compensation.

The difference only appears when the traction load is small or zero. In this scenario, almost all operating capacity of PFC is used for feeding renewable power to the grid, rather than for traction load compensation.

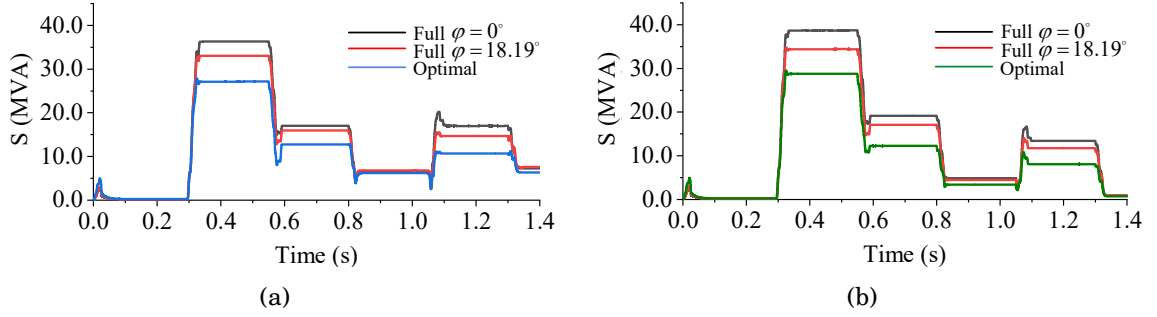


Figure 3.19: Comparison of operating capacity with renewable integration. (a) Renewable 6.5 MW. (b) Renewable 1 MW.

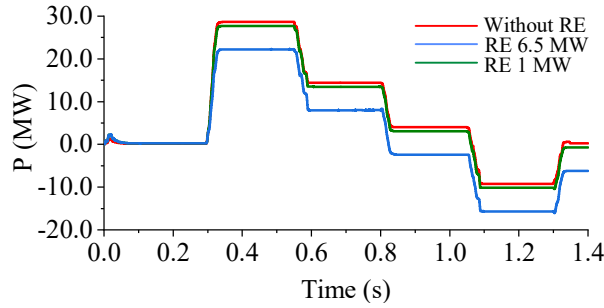


Figure 3.20: Active power from three-phase power grid

Under the optimal compensation strategy, Figure 3.20 illustrates the active power provided by the power grid at different cases. It is obvious that, when renewable energy is integrated, the reduced power from the power grid is approximately equal to the power from renewable energy, which shows the benefit of renewable energy integration for the traction power system. In the co-phase system, the power grid and renewable energy are combined and work together for the traction loads. On the one hand, renewable energy integration makes the traction power supply system less dependent on the power grid, even it can become profitable by feeding excessive power to the grid. On the other hand, PFC can not only be used for traction load compensation but also for the power grid connection of renewable energy, which saves additional converter construction costs.

Table 3.2: Optimization Results based on NSGA-II

Traction Load	30 MVA	15 MVA	4 MVA	-10 MVA	0 MVA
Without renewable	$\varphi_a = 18.19^\circ$ $\varphi_b = 11.57^\circ$ $\varphi_c = -2.95^\circ$ $K = 0.33$	$\varphi_a = 18.19^\circ$ $\varphi_b = 7.58^\circ$ $\varphi_c = -18.19^\circ$ $K = 0.25$	$\varphi_a = 18.19^\circ$ $\varphi_b = 7.58^\circ$ $\varphi_c = -18.19^\circ$ $K = 0.25$	$\varphi_a = 18.19^\circ$ $\varphi_b = 7.58^\circ$ $\varphi_c = -18.19^\circ$ $K = 0.25$	
Renewable 6.5MW	$\varphi_a = 18.19^\circ$ $\varphi_b = 13.30^\circ$ $\varphi_c = -8.01^\circ$ $K = 0.30$	$\varphi_a = 18.19^\circ$ $\varphi_b = 18.19^\circ$ $\varphi_c = -18.19^\circ$ $K = 0.22$	$\varphi_a = -14.85^\circ$ $\varphi_b = -18.19^\circ$ $\varphi_c = -18.19^\circ$ $K = 0.57$	$\varphi_a = 18.19^\circ$ $\varphi_b = -14.09^\circ$ $\varphi_c = -18.19^\circ$ $K = 0.30$	$\varphi_a = 18.19^\circ$ $\varphi_b = -18.19^\circ$ $\varphi_c = 0.00^\circ$ $K = 0.50$
Renewable 1MW	$\varphi_a = 18.19^\circ$ $\varphi_b = 12.00^\circ$ $\varphi_c = -3.70^\circ$ $K = 0.33$	$\varphi_a = 18.19^\circ$ $\varphi_b = 9.93^\circ$ $\varphi_c = -18.19^\circ$ $K = 0.24$	$\varphi_a = 18.19^\circ$ $\varphi_b = 15.63^\circ$ $\varphi_c = -18.19^\circ$ $K = 0.22$	$\varphi_a = 18.19^\circ$ $\varphi_b = 3.90^\circ$ $\varphi_c = -18.19^\circ$ $K = 0.26$	$\varphi_a = 18.19^\circ$ $\varphi_b = -18.19^\circ$ $\varphi_c = -0.02^\circ$ $K = 0.50$

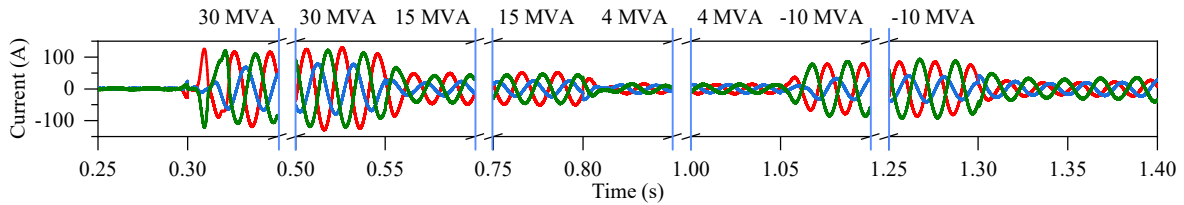


Figure 3.21: Three-phase currents in the presence of prediction error (Renewable 6.5 MW).

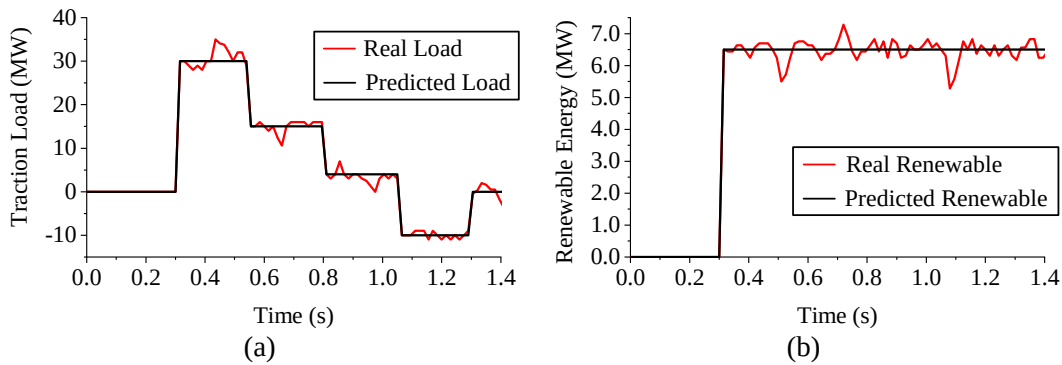


Figure 3.22: Prediction errors. (a) Load error. (b) Renewable error.

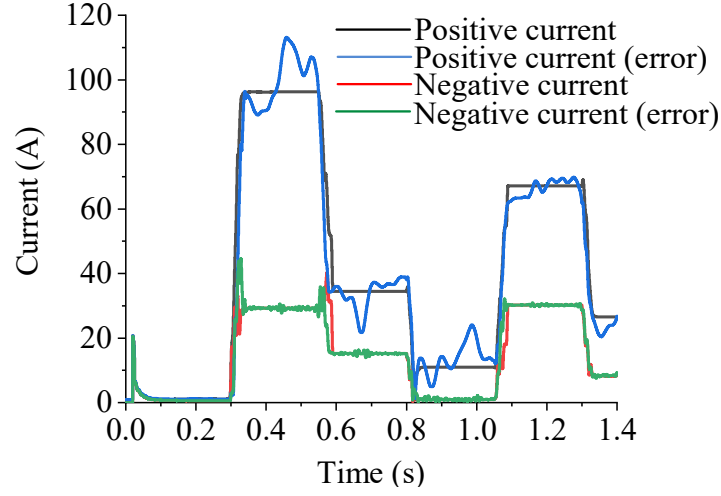


Figure 3.23: Comparison of positive and negative sequence currents

3.5.3 Validation of Hybrid Optimal Control In the Presence of Prediction Error

In this part, the performance of hybrid optimal control in the presence of prediction error is tested. The real-time error is introduced into the predictions of the traction loads and renewable energy (6.5 MW). The three-phase currents with prediction error are shown in Figure 3.21. The maximum error of traction loads and renewable energy is 5 MVA and 1 MW respectively, which is shown in Figure 3.22 (a) and (b). The black and red lines represent the predicted power, and the actual power of traction loads and renewable energy respectively. The difference between the red line and black line in each subfigure represents the predicted errors.

Figure 3.23 shows the comparison of the positive and negative sequence currents. It is noted that the positive sequence current with prediction error is unstable but the negative sequence current is almost the same as the current in which no prediction error exists. This implies that no extra negative sequence current is produced and injected into the three-phase power grid with the hybrid optimal control. The results verify that even in the presence of prediction errors, the voltage imbalance is still $< 2\%$.

3.6 Conclusion

In this chapter, an optimization strategy based on NSGA-II algorithm has been proposed for the co-phase system with renewable energy integration. A hybrid optimal compensation control has been developed to eliminate the negative sequence current caused by real-time prediction error. Extensive simulation experiments have been conducted to verify the effectiveness of the proposed NSGA-II based optimal compensation strategy. It has revealed that, compared with the full compensation strategy, the optimal compensation achieves better performance than traditional full compensation scheme regardless the renewable is integrated or not. The operating capacity of PFC is reduced and the power quality requirements are met. The simulation experiments show that the proposed method can achieve an average operating capacity reduction of more than 20%. Further, renewable energy integration decreases the power demand from the power grid. When the prediction error is considered, the traction power system imbalance will not become worse under the hybrid optimal compensation control.

While this chapter has investigated an optimal compensation scheme to support the operation of railway cophase systems integrated with renewable energies. It is clear that modern traction supply system systems are heavily supported by power electronic devices and energy storage systems which are prone to failures due to thermal stresses. To improve the life-span of these power electronic devices and energy storage systems while optimizing the overall system operation, the thermal management will be considered and a reinforcement learning based method will be investigated for the railway cophase system in next chapter.

THERMAL CONSTRAINED ENERGY OPTIMIZATION OF RAILWAY CO-PHASE SYSTEMS WITH ESS INTEGRATION - AN FRA-PRUNED DQN APPROACH

This chapter continues to concentrate on the railway co-phase traction power supply system (TPSS). To collect the regenerative energy and achieve a more flexible power flow, the energy storage system (ESS) is integrated into the co-phase system. As the key components, the reliability of power electronics modules in PFC and battery cells in ESS is highly related to their thermal performance. It is therefore vital to consider their operational thermal dynamics, leading to the proposal of a deep Q network (DQN) based thermal constrained energy management strategy in this chapter. Firstly, the system power flow model and electrothermal models for power electronics modules and battery cells are all established. Then, a DQN method is adopted to learn an optimized policy for peak power shaving while meeting temperature constraints. Finally, an FRA-based pruning method is proposed to reshape the agent to become more compact without sacrificing its performance. Case studies confirm that the proposed strategy can effectively reduce the peak traction power supply by up to 42.0%, and achieve up to 94.1% temperature reduction. The FRA-based pruning can achieve up to 89.9% agent

size reduction and 87.2% computation savings.

4.1 Introduction

The urbanization and industrialization trends worldwide have significantly increased the public transport demands, and the railway systems are playing an even more important role in urban and city transportation. Meanwhile, railway electrification has attracted much attention in recent years as a key part of the overall transportation decarbonization effort. Given the landscape of a significant increase in traction energy demand and the challenges of the overall decarbonization targets, it is vital to guarantee the traction power quality and enhance the stability of the power supply system [166].

The traditional single-phase 50 Hz/ 25 kV AC traction power supply system is widely deployed [167]. However this traditional power supply system may raise some concerns such as the three-phase imbalance, reactive power and neutral section issues [133]. To tackle these issues, a novel co-phase railway power supply system as shown in Figure 4.1 has been proposed and widely studied [168, 169], where a back-to-back converter acts as a PFC to compensate reactive power and balance the three-phase power grid. Meanwhile, the neutral sections can be eliminated. In [170], a 10MVA-rated co-phase system has been operated in China. Furthermore, braking of electrical multi-units (EMUs) will produce a large amount of regenerative energy which is undesirable to feed them back to the three-phase power grid. On the other hand, ESS is widely applied to collect regenerative energy and further provide the ancillary services such as spinning reserve, load shifting and power compensation [76, 132, 171]. For example, in [132], the ESS is integrated into the railway co-phase systems to obtain a minimum daily comprehensive cost and maximum regenerative utilization. In [76, 171], the hybrid energy storage system (HESS) is also integrated into the railway power supply system to smooth the fluctuations of traction/regenerative power. In this chapter, the ESS is integrated to regulate the high-power, dramatically-varying traction loads so as to achieve peak traction power shaving and smooth acceptance of regenerative power with the aid of the

smart energy management strategy. The co-phase system with ESS integration is shown in Figure 4.1.

As more power electronics modules and ESS have been applied in traction power supply systems for improving power quality, integrating renewables, smoothing traction load, and absorbing regenerative power, their lifespans may be significantly reduced due to poor thermal management, even leading to more frequent system failure events [129, 172]. For example, as reported in [172], the lifespan of the ESS will be reduced by two months per degree rise when the temperature is higher than 40°C. As demonstrated in [129], the failure rates of power converters are higher than those of other devices in railway power supply system, and more than 50% of the converter failures are caused by the insulated gate bipolar transistors (IGBTs) and freewheeling diodes. Thus it is vital to enhance the reliability and extend the lifespan of the ESS and power electronics modules. The ESS and PFC are among the key components of the railway co-phase systems as illustrated in Figure 4.1 to serve for the high voltage and high power traction loads, and the co-phase power supply system operation performance highly depends on the reliability of battery cells and power electronics modules including the IGBTs and diodes. Some researchers have discussed the reliability enhancement of ESS integrated into the railway system. For example, in [132], ESS degradation is considered to quantify the operation cost of the railway co-phase system. By optimizing the operation cost, the lifespan of ESS can be prolonged. In [133], a mixed-integer linear programming (MILP) optimization model with ESS degradation considered is formulated for the operation of the railway ESS-integrated co-phase system. However, as illustrated in [173, 174], besides the dynamics of the electrical systems, the failure rates of the battery cells and power electronics modules are highly related to the internal temperatures of the battery cells and the junction temperatures of the power electronics modules respectively. To control the thermal dynamics of the battery cells and power electronics modules, besides taking thermal capacity into consideration in the system design or applying an advanced cooling system [175–177], to develop a suitable thermal management strategy is an effective approach with the advantage that extra investment may not be required and

CHAPTER 4. THERMAL CONSTRAINED ENERGY OPTIMIZATION OF RAILWAY CO-PHASE SYSTEMS WITH ESS INTEGRATION - AN FRA-PRUNED DQN APPROACH

several thermal management strategies for the ESS and power electronics modules have been proposed. For the ESS, in [178], a multi-objective optimization framework is developed to optimize the charging patterns of the ESS in EVs with considering the temperature variations of the battery cells. In [172, 179], two energy management strategies using deep reinforcement learning (DRL) with battery temperature constraint for the hybrid electric buses are proposed. For the power electronics modules, a thermal balancing method by controlling the capacitor voltage of each submodule in the modular multilevel converter (MMC) is proposed in [180]. Furthermore, in [173], the power electronics module lifetime affected by the junction temperature is considered in the co-phase railway PFC control. By optimizing the single-phase space vector pulse width modulation (SVPWM), the average temperature and temperature fluctuation of the power electronics modules are reduced. In [129], a coordinated control strategy to alleviate thermal stress of the power electronics modules in PFC is proposed and applied in the railway co-phase system. However, the aforementioned thermal management strategies for the power electronics modules mainly focus on individual component-level control rather than system-level energy management. Few researchers have considered thermal management based on the electrothermal models for both the ESS and power electronics modules in the railway power supply system. Given that these two key devices are strongly coupled during the operation, it is vital to develop a unified energy management strategy for the railway co-phase system to optimize the power flow while meeting temperature constraints for both ESS and PFC.

DRL is an effective machine learning approach for decision-making and optimization problems, and it has attracted much attention due to its model-free features [181]. A large amount of studies have focused on the application of the DRL in intelligent transportation [172, 182–184], and smart energy management [185, 186]. For example, in [172], a knowledge-based, multiphysics-constrained energy management strategy for hybrid electric buses is proposed, with an emphasized consciousness of both thermal safety and degradation of the onboard lithium-ion battery (LIB) system. In [182, 183], two DRL methods have been developed respectively for optimizing the fast charging

procedure of the electric vehicles. In [184], a battery health-aware and DRL-based energy management framework is proposed for power-split hybrid electric vehicles in a naturalistic driving scenario. In [186], a model-free DRL method is proposed to optimize the battery energy arbitrage considering an accurate battery degradation model. Compared to the model-based methods, the DRL methods have demonstrated several distinctive advantages: 1) DRL algorithms are model-free and self-adaptable, and can learn the knowledge from historical data; 2) DRL algorithms can learn a good policy even under a very complex nonlinear environment with the aid of deep neural networks (DNNs). In this study, the thermal management for both the ESS and power electronics modules are considered and the formulated problem for optimizing the energy flow of the railway co-phase system is a complex nonlinear optimization problem subject to a number of nonlinear constraints. The linear programming techniques are difficult to solve this problem unless the nonlinear terms in the model are linearized. However linearization will inevitably reduce the model accuracy. The distinctive features of the DRL approaches offer great potentials to learn a smart energy management strategy from the complex nonlinear operational environment of the ESS integrated co-phase system. Even so, the aforementioned DRL-based methods still suffer from a bottleneck in real-life applications. That is the agent realized by the DNN requires large computation and memory resources, which limits its deployment in systems that have limited hardware resources [187]. Thus the agents trained by DNN-based DRL need to be more compact without sacrificing their performance.

This chapter aims to bridge the aforementioned research gaps and propose a novel unified FRA-pruned DQN-based thermal constrained energy management strategy to shave the peak traction power with the aid of the ESS, and reduce the reactive power injection into the three-phase power grid as much as possible. The main contributions are summarized as follows:

1. The model of the co-phase system with ESS integration is established. The power flow of the co-phase system is analysed and the compensation power of the PFC is derived based on the power of the ESS and phase angle of the three-phase power

grid.

2. The electrothermal models of the ESS and power electronics modules in the PFC are built respectively. The thermal dynamics can be analysed using the electrothermal models based on the compensation power of PFC and the power of ESS.
3. With the electrothermal models, an intelligent unified DQN-based energy management agent is developed to optimize the power flow of the co-phase system, so as to achieve the peak traction load shaving while meeting the temperature constraints for both ESS and power electronics modules.
4. A novel FRA-based pruning method for the DNN-based DQN agent is proposed. After reshaping, the agent becomes more compact with the redundant neurons in the DNN being removed. While the performance is guaranteed, and the computational complexity and required memory resources of the agent are significantly reduced.

The remainder of the chapter is organized as follows. In Section 4.2, the power flow model of the ESS integrated co-phase system is developed. The electrothermal models of ESS and power electronics modules in the PFC are also detailed. Section 4.3 formulates the optimization problem of thermal constrained energy management. The DQN-based thermal constrained energy management strategy is developed in Section 4.4. The FRA-based pruning method for the DQN agent is proposed in Section 4.4. Section 4.5 presents the case studies to verify the effectiveness of the proposed strategy. Section 4.6 concludes this chapter.

4.2 Model Formulation

4.2.1 Power Flow Analysis of ESS Integrated Co-phase System

As illustrated in Figure 4.1 (a), the railway power supply from the three-phase the grid is split into two single-phase channels by the V/V transformer, which is a traditional transformer configuration widely adopted in the railway traction system. One single-

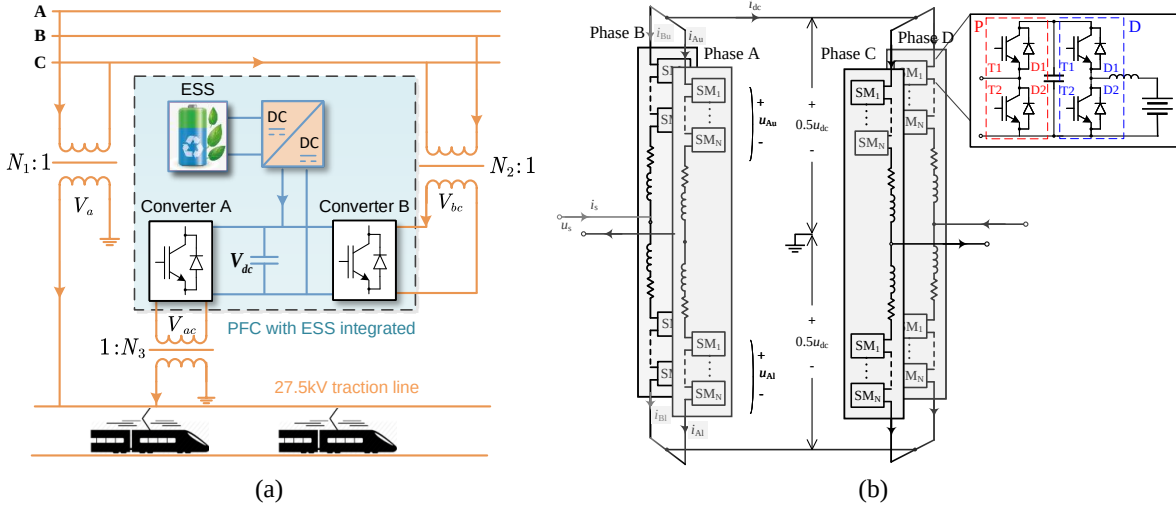


Figure 4.1: Railway co-phase system with ESS integration. (a) System structure; (b) Configuration of MMC-based PFC with ESS integration.

phase a connects to the traction line directly to feed traction loads. The back-to-back PFC is connected between phase bc and phase ac , which can balance the three-phase power grid, compensate the reactive power and suppress the harmonics. The configuration of PFC with ESS integration is shown in Figure 4.1 (b). The MMC is adopted for the high power compensation. The ESS is integrated into the co-phase system by connecting a set of battery cells with the submodules of MMC through a DC-DC converter. The ESS can achieve more flexibility for power flow management and provide ancillary services. In this chapter, in the premise of ensuring the balance of the three-phase power grid, the ESS is mainly utilized to achieve the load shifting so as to shave the traction/ regenerative peak power and smooth the traction loads.

The traction loads are inductive, which consume both active power and reactive power. Based on Figure 4.1 (a), one part of the traction loads is directly fed by the phase a of the power grid, and the other part is compensated by the PFC. Thus (4.1) can be obtained.

$$\begin{cases} P_L = S_L \cdot \cos \varphi_L = P_{ca} + P_a \\ Q_L = S_L \cdot \sin \varphi_L = Q_{ca} - Q_a \end{cases} \quad (4.1)$$

where S_L , P_L , Q_L and φ_L represent the apparent power, active power, reactive power and phase angle of the traction loads respectively. P_{ca} and Q_{ca} represent the active and

Furthermore, since the vector sum of the apparent power of the three-phase power grid equals zero, i.e. $\tilde{S}_a + \tilde{S}_b + \tilde{S}_c = 0$, the relationship between P_{cb} and P_L, P_{ESS} can be derived

$$P_{cb} = \alpha(P_L - P_{ESS})$$

$$= \frac{\cos\left(\frac{\pi}{6} + \varphi\right) \left(\sin\varphi \cdot \sin\left(\frac{\pi}{6} + \varphi\right) + \cos\varphi \cdot \cos\left(\frac{\pi}{6} + \varphi\right)\right) (P_L - P_{ESS})}{\sin\varphi \left(\cos\left(\frac{\pi}{6} + \varphi\right) \sin\left(\frac{\pi}{6} + \varphi\right) - \cos\left(\frac{\pi}{3} + \varphi\right) \sin\left(\frac{\pi}{3} + \varphi\right)\right) + \cos\varphi \left(\cos\left(\frac{\pi}{6} + \varphi\right)^2 + \sin\left(\frac{\pi}{3} + \varphi\right)^2\right)} \quad (4.3)$$

Then the compensation power of PFC can be expressed as (4.4) by substituting (4.3) into (4.2). It means that, once the power of ESS and phase angle of the power grid are determined, the corresponding compensation power of PFC is determined accordingly based on the traction loads.

$$\begin{cases} P_{ca} = \alpha P_L + (1 - \alpha) P_{ESS} \\ Q_{ca} = Q_L + \tan\left(\frac{\pi}{6} - \varphi\right) (1 - \alpha) (P_L - P_{ESS}) \\ P_{cb} = \alpha (P_L - P_{ESS}) \\ Q_{cb} = \tan\left(\frac{\pi}{6} + \varphi\right) \alpha (P_L - P_{ESS}) \end{cases} \quad (4.4)$$

4.2.2 Electrothermal Model of Power Electronics modules

4.2.2.1 Modeling of PFC and DC-DC converter

The back-to-back MMC-based PFC with ESS integration as shown in Figure 4.1 (b) can be seen as the combination of two single-phase MMCs labeled as converters A and B respectively. Both single-phase MMCs act as the inverter and rectifier respectively under the specific operation modes. As shown in Figure 4.1 (b), each submodule in the single-phase MMC includes four IGBTs and four diodes. Two sets of IGBTs and diodes in Figure 4.1 (b), labeled as P-T1, P-D1, P-T2, and P-D2, mainly perform the function of PFC such as power compensation. Thus the converter made of P-T1, P-D1, P-T1, and P-D2 is called as PFC converter for convenience. Another two sets of IGBTs and diodes, labeled as D-T1, D-D1, D-T2, and D-D2, constitute the DC-DC converter to connect the battery cells with the PFC.

CHAPTER 4. THERMAL CONSTRAINED ENERGY OPTIMIZATION OF RAILWAY CO-PHASE SYSTEMS WITH ESS INTEGRATION - AN FRA-PRUNED DQN APPROACH

In the following, the modeling of PFC and DC-DC converters is discussed separately. To facilitate the analysis, take the inverter mode of the single-phase MMC as an example. When the single-phase MMC is operated in the inverter mode, the AC side current is evenly distributed through the upper and lower arms. Assume the AC side voltage u_s and current i_s as:

$$\begin{cases} u_s = U_m \sin(\omega t) \\ i_s = I_m \sin(\omega t - \phi) \end{cases} \quad (4.5)$$

where U_m and I_m are the maximum amplitudes of the voltage and current of the AC side. ω is the AC frequency and ϕ is the phase angle of the AC side in the MMC. Based on the aforementioned analysis, when the compensation power of the PFC is determined, I_m can be easily obtained based on the compensation power and port voltages of the PFC.

As shown in Figure 4.1 (b), taking phase A of the single-phase MMC as an example, the voltages u_{Au} , u_{Al} and currents i_{Au} , i_{Al} of the upper arm and lower arm of the phase A can be expressed as

$$\begin{cases} u_{Au} = \frac{U_{dc}}{2} - u_s, u_{Al} = \frac{U_{dc}}{2} + u_s \\ i_{Au} = \frac{I_{dc} + i_s}{2}, i_{Al} = \frac{I_{dc} - i_s}{2} \end{cases} \quad (4.6)$$

where U_{dc} and I_{dc} represent the voltage and current of the DC side.

Since the active power on the DC side should be equal to that from the AC side, it yields

$$U_{dc}I_{dc} = \frac{U_m}{\sqrt{2}} \cdot \frac{I_m}{\sqrt{2}} \cdot \cos \phi = \frac{1}{2}U_m I_m \cos \phi = \frac{1}{4}mU_{dc}I_m \cos \phi \quad (4.7)$$

where $m = \frac{2U_m}{U_{dc}}$ is the modulation ratio. Thus it has

$$I_{dc} = \frac{1}{4}mI_m \cos \phi \quad (4.8)$$

Substitute (4.5) and (4.8) into (4.6), then

$$\begin{cases} i_{Au} = \frac{1}{8}mI_m \cos \phi + \frac{1}{2}I_m \sin(\omega t - \phi) \\ i_{Al} = \frac{1}{8}mI_m \cos \phi - \frac{1}{2}I_m \sin(\omega t - \phi) \end{cases} \quad (4.9)$$

According to [188], the duty ratio of the upper and lower arms can be given as

$$\begin{cases} n_{Au} = \frac{1}{2}(1 - m \sin(\omega t)) \\ n_{Al} = \frac{1}{2}(1 + m \sin(\omega t)) \end{cases} \quad (4.10)$$

To further estimate the thermal stresses of each power electronics module in PFC, the average and root-mean-square (RMS) currents of the IGBTs and diodes need to calculate. Take the upper arm as an example, assume the AC side current reaches zero when the phase angles are θ , $\pi + 2\phi - \theta$, $2\pi + \theta$ within a fundamental-frequency period. The working time is $(\pi + 2\phi - \theta, 2\pi + \theta)$ for P-T1 and P-D2, and $(\theta, \pi + 2\phi - \theta)$ for P-T2 and P-D1. Therefore, the average and RMS currents of P-T1 can be expressed as

$$i_{P-T1,ave} = \frac{1}{2\pi} \int_{\pi+2\phi-\theta}^{2\pi+\theta} n_{Au} i_{Au} d(\omega t) \quad (4.11)$$

$$i_{P-T1,rms}^2 = \frac{1}{2\pi} \int_{\pi+2\phi-\theta}^{2\pi+\theta} n_{Au} i_{Au}^2 d(\omega t) \quad (4.12)$$

The average and RMS currents of P-T2 and P-D1, P-D2 can be also calculated based on (4.9) and (4.10). The calculation equations have been detailed in [188], and are therefore omitted in this chapter.

Besides, for the devices D-T1, D-T2 and D-D1, D-D2 used for the DC-DC conversion, the average and RMS currents are mainly related to the duty ratio D , output current I_0 and current ripple ratio r . The corresponding relationships can be expressed as

$$i_{D-T1,2/D-D1,2,ave} = f_{ave}^{DC}(D, I_0) \quad (4.13)$$

$$i_{D-T1,2/D-D1,2,rms} = f_{rms}^{DC}(D, I_0, r) \quad (4.14)$$

where $D = 1 - \frac{V_I}{V_o}$ when the DC-DC converter is operated at the Boost mode and $D = \frac{V_o}{V_I}$ at the Buck mode. V_I and V_o are the port voltages of the DC-DC converter. The output current I_0 can be calculated based on the battery power P_{ESS} and the DC voltage V_o . f_{ave}^{DC} and f_{rms}^{DC} define the relationships between the average and RMS currents and the parameters D , I_0 and r , and please refer to [189] for details.

4.2.2.2 Loss model

The losses of the power electronics modules include conduction loss and switching loss.

The conduction loss can be estimated as follows:

The conduction losses of IGBTs and diodes are determined by the voltage drop in IGBTs/diodes and the current flowing through them. The voltage drop V_{ce} of IGBT or diode at the junction temperature T_j can be expressed as:

$$V_{ce}(T_j) = V_{ce0}(T_j) + R_{ce0}(T_j)I_C \quad (4.15)$$

By fitting the relationship between $V_{ce}(T_j)$ and I_C at the temperatures T_u and T_l (generally $T_u = 125^\circ\text{C}$ and $T_l = 25^\circ\text{C}$), two sets of parameters ($V_{ce0}(T_u)$, $R_{ce0}(T_u)$) and ($V_{ce0}(T_l)$, $R_{ce0}(T_l)$) can be obtained. Generally speaking, both sets of parameters are provided by the official datasheets of the power electronics modules. The function of $V_{ce0}(T_j)$ and $R_{ce0}(T_j)$ at T_j can be approximated by interpolation as follows:

$$V_{ce0}(T_j) = (V_{ce0}(T_u) - V_{ce0}(T_l))(T_j - T_l)/100 + V_{ce0}(T_l) \quad (4.16)$$

$$R_{ce0}(T_j) = (R_{ce0}(T_u) - R_{ce0}(T_l))(T_j - T_l)/100 + R_{ce0}(T_l) \quad (4.17)$$

Thus the conduction loss of IGBT or diode is given as:

$$P_{con.T/D}(T_j, I_{ave}, I_{rms}) = \frac{1}{T_j} \int_0^T V_{ce}(T_j) I_C dt = V_{ce0}(T_j) |I_{ave}| + R_{ce0}(T_j) I_{rms}^2 \quad (4.18)$$

where I_{ave} and I_{rms} can be obtained based on (4.11)-(4.12) for the IGBT and (4.13)-(4.14) for the diode.

Besides, at the switching instant, the operations of turning on/off for IGBTs and diodes will produce the switching losses which can be estimated by:

$$P_{sw.T} = f_{sw} E_{on+off} \left(\frac{I_{ave}}{I_{ref}} \right)^{K_{i.T}} \left(\frac{V_{DC}}{V_{ref}} \right)^{K_{v.T}} \cdot (1 + C_{E.T}(T_j - T_{ref})) \quad (4.19)$$

$$P_{sw.D} = f_{sw} E_{rr} \left(\frac{I_{avg}}{I_{ref}} \right)^{K_{i.D}} \left(\frac{V_{DC}}{V_{ref}} \right)^{K_{v.D}} \cdot (1 + C_{E.D}(T_j - T_{ref})) \quad (4.20)$$

where f_{sw} is switching frequency, I_{ref} , V_{ref} , and T_{ref} are the reference current, voltage, and temperature respectively, when the switching loss is measured as given in the

datasheet. E_{on+off} is the turn-on and turn-off losses of IGBT under rated voltage and rated current. E_{rr} is the turn-on and turn-off losses of FWD under rated voltage and rated current. K_v and K_i are the correction coefficient for voltage and current dependency of the switching loss. $C_{E,T}$ and $C_{E,D}$ are the temperature coefficients of switching loss for IGBT and diode respectively.

In summary, the total power losses of the IGBT or diode are given as

$$P_{T.IGBT/D} = P_{con.T/D} + P_{sw,T/D} \quad (4.21)$$

4.2.2.3 Thermal estimation

The equivalent thermal networks of the power electronics module can be divided into two types either a Cauer model or a Foster model. Based on [188], for the Cauer model, the material property and geometry of the device are normally required to calculate the related parameters, which in many cases are difficult to obtain. While the parameters of the Foster model are easy to identify and usually provided in the datasheet. Therefore, the Foster model, as shown in Figure 4.3, is used as the equivalent thermal network to estimate the junction temperature which is given by

$$T_{j.IGBT} = P_{T.IGBT} Z_{j-h.IGBT} + T_h \quad (4.22)$$

$$T_{j.D} = P_{T.D} Z_{j-h.D} + T_h \quad (4.23)$$

$$T_h = (P_{T.IGBT} + P_{T.D}) Z_{h-a} + T_a \quad (4.24)$$

where $T_{j.IGBT}$ and $T_{j.D}$ represent the junction temperatures of the IGBT and diode respectively. T_h represents the temperature of the heat sink. T_a represents the ambient temperature. $Z_{j-h.D}$ and $Z_{j-h.IGBT}$ represent the equivalent thermal networks of the IGBT and diode between the junction and heat sink. Z_{h-a} represents the equivalent thermal network between the heat sink and ambient. It should be noted that the thermal network $Z_{j-h.D/IGBT}$ has considered both thermal networks $Z_{j-c.D/IGBT}$ between the diode/IGBT and case, and $Z_{c-h.D/IGBT}$ between the case and heat sink. That means. in this chapter, the aggregated parameters for $Z_{j-h.D/IGBT}$ combining $Z_{j-c.D/IGBT}$ and

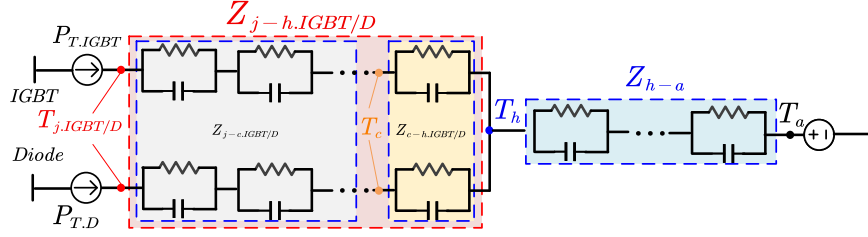


Figure 4.3: Thermal network of power electronics modules.

$Z_{c-h,D/IGBT}$ are adopted. The detailed parameters adopted in this chapter can be found in [190, 191].

The thermal network in Figure 4.3 reflecting the thermal dynamics can be expressed by

$$Z = \sum_{i=1}^n R_{th_i} \left(1 - e^{-\frac{t}{\tau_{th_i}}} \right) \quad (4.25)$$

where n is the order number of the thermal model and R_{th_i} is the thermal resistance. τ_{th_i} is the time constant of each RC network depending on R_{th_i} and C_{th_i} , and the relationship is given by

$$\tau_{th_i} = R_{th_i} \times C_{th_i} \quad (4.26)$$

4.2.3 Electrothermal Model of ESS

The ESS is an important component in achieving more flexibility in the power flow. In this part, an electrothermal model of the ESS is adopted. The temporal evolution of the state of charge (SoC) can be formulated in a discrete form

$$SoC(k+1) = SoC(k) + \frac{I(k) \cdot T_s}{3600 C_{ESS}} \quad (4.27)$$

where $I(k)$ represents the charging/discharging current at time step k . C_{ESS} is the rated capacity of the ESS. T_s is the sampling time.

To model the electrothermal characteristics of the battery cells in ESS, a transient-state equivalent electric circuit model is adopted to represent the battery cell, which is shown in Figure 4.4. This first-order simplified thermal model is widely adopted in the battery thermal modeling field [192], where the OCV is the battery open-circuit

voltage, R represents the battery internal resistance. The RC network to capture the battery relaxation process is set to a constant network since the model accuracy can be guaranteed without being highly affected by factors such as SoC, temperature and current [192]. V and I are the terminal voltage and current of the battery cell. The reference directions of the current and voltage are shown in Figure 4.4. When the actual directions of the current and voltage are in alignment with the labeled reference directions, the battery is operated in the discharging state and the output power is positive correspondingly. Conversely, when the actual direction of the current is opposite to its referenced direction, the battery is in the charging state and the output power is negative.

Based on [192], battery OCV is mainly dependent on the battery SoC and insensitive to the temperature variations, e.g. less than 10mV as temperature changes from -10°C to 50°C . Also as stated in [193], the variation of battery OCV in terms of ambient temperature is negligible in the middle and high ranges of SoC (from 20% to 100% SoC) especially when the temperature is higher than 0°C . Thus the battery OCV can be expressed as follows:

$$OCV(k) = f_{OCV}(SoC(k)) \quad (4.28)$$

The battery internal resistance R depends on the battery internal temperature as expressed in (4.29).

$$R(k) = f_R(T_{in}(k)) \quad (4.29)$$

Suppose the over-potential across the RC network shown in Figure 4.4 is v_1 , and that the load current keeps constant during the sampling period. Based on the dynamics

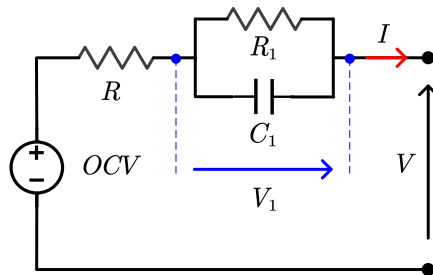


Figure 4.4: Battery electric circuit model.

of the RC network, (4.30) is given.

$$V_1(k+1) = a_1 V_1(k) + b_1 I(k) \quad (4.30)$$

where a_1 and b_1 are the electrical circuit model parameters identified by curve fitting the experimental data.

The terminal voltage of the battery cell can be given as

$$V(k) = f_{OCV}(SoC(k)) + f_R(T_{in}(k)) \cdot I(k) + V_1(k) \quad (4.31)$$

Based on the principle of power balance for the circuit shown in Figure 4.4, the charging/discharging power of the battery cells can be given by

$$P_{ESS}(k) = I(k)OCV(k) - R(k)I^2(k) - I(k)V_1(k) \quad (4.32)$$

where $P_{ESS}(k)$ is the charging/discharging power at time step k . $P_{ESS}(k) < 0$ represents the charging to the ESS, $P_{ESS}(k) > 0$ represents the discharging from the ESS. Then the charging/discharging current can be obtained by solving (4.32), yielding

$$I = \frac{(OCV - V_1) - \sqrt{(OCV - V_1)^2 - 4R \cdot P_{ESS}}}{2R} \quad (4.33)$$

To estimate the internal temperature of the battery cell, two parts of the battery thermal model are considered: thermal generation and thermal transfer. Based on [192], under large terminal current, the battery heat generation is dominated by the ohmic heat generated over the internal resistance R of the battery cell. The battery heat generation is proportional to the square of the terminal current and thus given as

$$Q = I^2 \cdot R \quad (4.34)$$

Taking the terminal current (4.33) into (4.34), heat generation can be obtained. As stated in [194, 195], when the charging/ discharging rate of the battery is lower than 1C, the temperature distribution of the battery is relatively uniform. In this chapter, the limit of the ESS charging/ discharging rate is 1C and the operation under 1C for ESS will not last more than 15 mins. Thus, to build a simplified lump thermal model, it

is acceptable to assume that the battery shell temperature and internal temperature are both uniform, and heat generation is uniformly distributed within the battery. Heat conduction is assumed to be the only heat transfer between the battery internal and shell, and between the battery shell and the ambience. Thus the thermal model of the battery cell is given as

$$C_1 \frac{dT_{in}}{dt} = Q - k_1 \cdot (T_{in} - T_{sh}) \quad (4.35)$$

$$C_2 \frac{dT_{sh}}{dt} = k_1 \cdot (T_{in} - T_{sh}) - k_2 \cdot (T_{sh} - T_{amb}) \quad (4.36)$$

where T_{in} and T_{sh} are battery internal (core) and shell temperature, respectively; T_{amb} is the ambient temperature in the unit of $^{\circ}\text{C}$; C_1 , C_2 are the battery internal and shell thermal capacity in the unit of $\text{J}/^{\circ}\text{C}$, respectively; Q is the heat generation rate in unit of W which is dominated by the ohmic heat in (4.34); k_1 is the heat conductivity coefficient inside of the battery in the unit of $\text{W}/(\text{m} \cdot \text{K})$, and k_2 the convective heat conductivity coefficient of the battery shell with ambience. Discretizing (4.35) and (4.36), the internal and shell temperatures of the battery cell can be expressed as (4.37) by substituting (4.33) into (4.34).

$$\begin{bmatrix} T_{in}(k+1) \\ T_{sh}(k+1) \end{bmatrix} = \begin{bmatrix} 1 - T_s \cdot \frac{k_1}{C_{q1}} & T_s \cdot \frac{k_1}{C_{q1}} \\ T_s \cdot \frac{k_1}{C_{q2}} & 1 - T_s \cdot \frac{k_1 + k_2}{C_{q2}} \end{bmatrix} \cdot \begin{bmatrix} T_{in}(k) \\ T_{sh}(k) \end{bmatrix} + \begin{bmatrix} T_s \cdot \frac{f_R(T_{in}(k)) \cdot I^2(k)}{C_{q1}} \\ T_s \cdot \frac{k_2 \cdot T_{amb}}{C_{q2}} \end{bmatrix} \quad (4.37)$$

The established model has been validated with high fidelity. As being confirmed in [192, 196], the root-mean-square error (RMSE) of the thermal voltage is around 3.4mV , which is equivalent to 0.1% of the battery nominal voltage. The internal temperature modeling RMSE is 0.37°C and the maximum error is 1.28°C . Therefore, the accuracy of the established electrothermal model is acceptable. The electrothermal model can hence be used as a good benchmark for battery packs in real-life applications.

4.3 Problem formulation

In this chapter, the optimization objectives aim to compensate the reactive power of the traction loads by utilizing the PFC to satisfy the power quality requirements, as well as

to shave the peak traction power and smooth the regenerative power with the aid of the integrated ESS. Meanwhile, to enhance the system reliability and increase the lifespan of both the power electronics modules and the integrated ESS, temperature constraints are also considered in the optimization.

A Markov Decision Process (MDP) model with a discrete-time step is built. The whole sequential decision-making process of the MDP model can be described as follows: given a set of states s_k at time step k which includes ESS states, power electronics module temperature states, traction load states, and ambient temperature, the agent selects a set of actions from an action-space $a_k \in A$ based on the policy π . The goal of the proposed algorithm is to find the optimal policy to achieve the proposed optimization objectives. The MDP is formulated as:

4.3.1 State Space

For the PFC converters (Converters A and B) and DC-DC converters in the co-phase system with ESS integration, the state space at time instant k is defined as $s_{k.Con} = (T_{Con.A}(k), T_{Con.B}(k), T_{Con.DC}(k))$, where $T_{Con.A}(k)$, $T_{Con.B}(k)$ and $T_{Con.DC}(k)$ represent the temperatures of the converter A, converter B in PFC, and DC-DC converter respectively. It is assumed that the heat is uniformly distributed within the converters. Thus the temperature of each submodule in the converters can be regarded as the same. Furthermore, each submodule of the PFC converters and DC-DC converters includes two IGBTs and two diodes as shown in Figure 4.1 (b). The maximum value of the temperatures of the IGBTs and diodes in each submodule is seen as the temperature of the submodule, also the temperature of the converter, i.e.

$$\begin{cases} T_{Con.A}(k) = \max(T_{PA-T1/T2}(k), T_{PA-D1/D2}(k)) \\ T_{Con.B}(k) = \max(T_{PB-T1/T2}(k), T_{PB-D1/D2}(k)) \\ T_{Con.DC}(k) = \max(T_{D-T1/T2}(k), T_{D-D1/D2}(k)) \end{cases} \quad (4.38)$$

The temperature states of the converters defined in (4.38) at each time instant can be obtained by (4.22)-(4.24). For the ESS, the state space at time instant k is defined as

$s_{k.ESS} = (SoC(k), T_{in}(k), T_{sh}(k))$. It is also assumed that the charging/discharging power and temperature are uniformly distributed within the whole ESS. Thus the states of each battery cell can stand for the states of the whole ESS. The state transition function reflecting the electrothermal dynamics of the ESS from k to $k + 1$ is defined in (4.27) and (4.37). Besides, for the traction loads, the state of $s_{k.L} = (S_L(k), P_{ave.L}(k))$ includes the apparent traction power and average active traction power. The power factor of the traction loads is set to 0.95 based on [197]. Finally the ambient temperature is defined as $s_{k.amb} = T_{amb}(k)$. The state in the MDP at the time instant k can be expressed as $s_k = (s_{k.Con}, s_{k.ESS}, s_{k.L}, s_{k.amb})$

4.3.2 Action Space

As stated in Section 4.2.1, once the phase angle φ and the power of ESS are determined, the power flow can be calculated accordingly. The size of the actions is a hyper-parameter. If the size is too small, the actions are not fine-grained, and the agent may have difficulties to reach a specific location with more accuracy. While if the size is too large, it may slow down the learning process or lead to sub-optimal solutions as it takes more steps to reach a specific targeted location. Generally speaking, the more choices are designed for the space discrete actions, the worse for the algorithm convergence. Based on these considerations, the action space of the ESS is discretized into 9 actions as

$$a_{k.ESS} = (-1, -0.75, \dots, 0, \dots, 0.75, 1)P_{ESS}^{\max} \quad (4.39)$$

where $P_{ESS}^{\max}$ is the maximum discharging/charging power. The action space of phase angle is defined as

$$a_{k.\varphi} = (-1, -0.8, \dots, 0, \dots, 0.8, 1)\varphi_{\max} \quad (4.40)$$

where there are 11 actions in total, $\varphi_{\max}$ is the maximum allowable phase angle which also reflects the maximum reactive power feeding into the three-phase power grid. $\varphi_{\max}$ is set to 20° based on the requirements [197]. Thus the whole action space $a_k = (a_{k.ESS}, a_{k.\varphi})$ includes 9×11 actions in total, and the action intervals are set to be 1 MW

for the ESS and 2° for the phase angle, which are fine-grained and reasonable according to the findings in [198, 199].

4.3.3 Reward

The design of the reward significantly affects the optimization results. To achieve the optimization objectives illustrated above, the reward at time step k is defined as (4.41).

$$R_k = - \left(\underbrace{a \Delta P(k)}_{load\ shifting} + \underbrace{b \rho_{pa}(k)}_{phase\ angle} + \underbrace{c \rho_T(k)}_{thermal} + \underbrace{d \rho_{SoC}(k)}_{SoC} \right) \quad (4.41)$$

where a , b , c and d are the weighting factors implying the different importance of the objectives and also enforcing the objectives dimensionally compatible with each other.

In (4.41), the first part $\Delta P(k)$ considers the peak load shaving. It is defined as

$$\Delta P(k) = |P_{ave.L}(k) - (P_L(k) - P_{ESS}(k))| \quad (4.42)$$

where $P_{ave.L}(k)$ represents the average power of the traction loads during the timeslot $[0, k]$. When $\Delta P(k)$ is reduced, it means the power from the three-phase power grid is smoother. The second part in (4.41) is the penalty term for the phase angle, which is defined as (4.43) to reduce the phase angles so that the lower reactive power is fed into the three-phase power grid.

$$\rho_{pa}(k) = |\varphi(k)| \quad (4.43)$$

The third part $\rho_T(k)$ in (4.41) is the thermal penalty term of the converters and ESS, which is defined as

$$\rho_T(k) = \sum \rho_{T(\cdot)}(k) \quad (4.44)$$

$$\rho_{T(\cdot)}(k) = \begin{cases} 0 & \text{if } T(\cdot) \leq T(\cdot)_{lim} \\ T(\cdot) - T(\cdot)_{lim} & \text{if } T(\cdot) > T(\cdot)_{lim} \end{cases} \quad (4.45)$$

where $(\cdot)$ represents the ESS or converters. $T(\cdot)_{lim}$ is the temperature limit for the ESS or converters.

In (4.41), the term $\rho_{SoC}(k)$ is an indicator used for the SoC limit, which is defined as

$$\rho_{SoC}(k) = \begin{cases} 0 & \text{if } SoC^{\min} \leq SoC \leq SoC^{\max} \\ 1 & \text{otherwise} \end{cases} \quad (4.46)$$

The objective function, i.e. the cumulative rewards over the whole optimization process is denoted as:

$$\max f = \sum_0^K R_k \quad (4.47)$$

4.3.4 Constraints

In the formulated optimization problem, the constraints for the operation of railway co-phase system integrated with ESS are considered below. The power balance constraint can be found in (4.1) and (4.2). For the converters and ESS, the temperature limit can be expressed as (4.48) and considered as a soft constraint in (4.47). The power limit (4.49) of the ESS is imposed in the action space, and the SoC limit of the ESS can be expressed as (4.50) and added in (4.47) as the hard constraints by setting a rather large weighting factor.

$$T(\cdot) \leq T(\cdot)_{\lim} \quad (4.48)$$

$$0 \leq |P_{ESS}| \leq |P_{ESS}^{\max}| \quad (4.49)$$

$$SoC^{\min} \leq SoC \leq SoC^{\max} \quad (4.50)$$

4.4 Methodology

In this section, based on the formulated MDP, a DRL-based thermal constrained energy management strategy is proposed to solve the formulated problem in Section 4.3. Moreover, an FRA-based pruning method is developed to reshape the DRL agent and make the agent more compact without sacrificing its performance.

4.4.1 Prioritized DQN

The deep Q-learning network (DQN) originated from the original Q-learning algorithm is one of the state-of-the-art DRL algorithms. Q-learning is a model-free RL algorithm aiming at training an agent to find the best policy with a set of given states by exploring the environment [186]. The action taken under a specific set of given states is determined by the action-value Q function which is denoted by $Q_\pi(s, a)$ defined as

$$Q_\pi(s, a) = \mathbb{E}_\pi \left[\sum_0^K \gamma^k \cdot R_k | s_k = s, a_k = a \right] \quad (4.51)$$

where γ is the discount factor. The policy π maps from the current states to the specific actions.

To find the best policy π^* , the Q function $Q_\pi(s, a)$ needs to be literately updated by interacting with the environment based on the following Bellman equation:

$$Q(s_k, a_k) \leftarrow Q(s_k, a_k) + \alpha \left[\left(R_k + \gamma \max_a Q(s_{k+1}, a_{k+1}) \right) - Q(s_k, a_k) \right] \quad (4.52)$$

where α is the learning rate. $Q(s, a)$ is approximated by a look-up table characterized by a set of states and actions. When the iteration reaches the preset value, it can be considered that $Q(s, a)$ converges to the approximate optimal Q-value $Q_\pi^*(s, a)$. Then the action will be taken based on the most updated $Q(s, a)$ by using ϵ -greedy strategy. The rule is the action $a_k = \underset{a}{\arg \max} Q(s, a)$ is taken with the probability $1-\epsilon$ or a random action is selected with the probability ϵ [127].

However, Q-learning will face a serious challenge, that is when the state and action space is high-dimensional, the built look-up table is rather large. To address this challenge, an algorithm proposed by Deepmind [127] is to use DNN to approximate the optimal Q-value function $Q_\pi^*(s, a)$ rather than a lookup table. The approximated optimal action-value Q function by the DNN can be denoted by

$$Q(s, a, \omega) \approx Q_\pi^*(s, a) \quad (4.53)$$

where ω is the weights of the neural network. During the training process of DQN, the weights are updated by minimizing the mean square error (MSE) loss between the values of Q target and Q predict:

$$L(\omega) = \mathbb{E}[\underbrace{(R_k + \gamma \max_{a_{k+1}} Q(s_{k+1}, a_{k+1}, \omega^-))}_{Q \text{ target}} - \underbrace{Q(s, a, \omega)}_{Q \text{ predict}}]^2 \quad (4.54)$$

The Q target value is $y_k = R_k + \gamma \max_{a_{k+1}} Q(s_{k+1}, a_{k+1}, \omega^-)$, where $Q(s_{k+1}, a_{k+1}, \omega^-)$ is a separate neural network namely target network. The weights ω^- in the target network are updated periodically by copying the weights ω in the predict network $Q(s, a, \omega)$ to replace the previous weights ω^- .

In the DQN training process, the recent experiences (s_k, a_k, R_k, s_{k+1}) are stored in the experience replay pool. In each training step, a batch of samples are uniformly selected from the experience replay pool for the DNN-based agent training based on (4.54). However, due to the limit of the size for the experience replay pool, the memory only stores recent M samples by removing the oldest experiences for allocating a space for the latest ones. However, it is highly likely that the experiences with higher impact on the learning are forgot during the above process. To resolve this challenge, a new technique prioritizing significant experiences is proposed in [200] by changing the sampling distribution of DQN training. The overall idea for prioritized experience replay is that the samples with higher TD error obtains higher ranking in terms of probability than the other samples. Then in the training process, the experiences are stochastically sampled based on the assigned probabilities. In the case studies presented in this chapter, such prioritized DQN is adopted.

4.4.2 FRA-based Pruning Method for DQN Agent

In the field of system identification, a structure, namely linear-in-the-parameter model, is widely adopted for approximating a large class of nonlinear systems. Such nonlinear models form a linear combination of model terms, or basis functions, which are nonlinear functions of the system variables. However, one problem with such models is that an excessive number candidate model terms or basis functions have to be considered, which may lead to high computational complexity or over-fitting. To handle this issue, the model selection algorithms have been proposed to build parsimonious and compact models with a much smaller number of model terms. Among theses algorithms, a particular one,

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namely fast recursive algorithm (FRA), was proposed to fast select the most significant model terms as well as identify the model parameters [201]. The FRA is introduced below. Consider a nonlinear discrete-time dynamic system denoted by a linear-in-the-parameter model as (4.55), which is identified by N data samples $\{x(i), y(i)\}_{i=1}^N$

$$y = \Psi\Theta + \Xi \quad (4.55)$$

where $y = [y(1), \dots, y(N)]^T \in \mathbb{R}^N$ represents the system outputs. $\Psi = [\varphi_1, \dots, \varphi_j, \dots, \varphi_S] \in \mathbb{R}^{N \times S}$ is the regression matrix containing all candidate model terms. In the regression matrix, each element $\varphi_j = [\varphi_j(x(1)), \dots, \varphi_j(x(N))]^T \in \mathbb{R}^{N \times 1}$ ($j = 1, \dots, S$) represents a specific nonlinear function of the N inputs. $\Theta = [\theta_1, \dots, \theta_S]^T \in \mathbb{R}^S$ is the parameter matrix including S unknown system parameters to be identified. $\Xi = [\varepsilon(1), \dots, \varepsilon(N)]^T \in \mathbb{R}^N$ is the system residual matrix.

Before introducing the principle of FRA, two recursive matrices, M_k and R_k , are predefined as (4.56) and (4.57) to facilitate the further demonstration of the fast model term selection and parameter identification.

$$M_k = \Psi_k^T \Psi_k \quad (4.56)$$

$$R_k = 1 - \Psi_k M_k^{-1} \Psi_k^T \quad (4.57)$$

where $\Psi_k \in \mathbb{R}^{N \times k}$ ($k = 1, \dots, S$) is the submatrix containing the first k columns of the regression matrix Ψ . Notably, it is defined that $R_0 = 1$.

To identify the system parameters, a cost function as (4.58) can be defined

$$\min E(\Theta) = (\Psi\Theta - y)^T (\Psi\Theta - y) \quad (4.58)$$

Generally, when the first k columns in matrix Ψ are selected, the parameter matrix $\hat{\Theta}_k \in \mathbb{R}^k$ that minimizes the cost function (4.58) can be estimated as (4.59) by the least square method if Ψ_k is of full column rank.

$$\hat{\Theta}_k = M_k^{-1} \Psi_k^T y \quad (4.59)$$

The minimal cost function associated with $\hat{\Theta}_k$ can be reformulated as

$$E_k = y^T y - \hat{\Theta}_k^T \Psi_k^T y = y^T R_k y \quad (4.60)$$

Based on (4.60) and the properties of R_k given in [201], it follows that

$$\begin{cases} E_{k+1} = y^T R_{k+1} y = E_k - \frac{y^T R_k \varphi_{k+1} \varphi_{k+1}^T R_k^T y}{\varphi_{k+1}^T R_k \varphi_{k+1}} \\ E_0 = y^T y \end{cases} \quad (4.61)$$

Furthermore, to simplify the computational complexity, three quantities are defined as follows

$$\begin{cases} \varphi_j^{(k)} \triangleq R_k \varphi_j, \varphi_j^{(0)} \triangleq R_0 \varphi_j = \varphi_j \\ a_{k,j} \triangleq \left(\varphi_k^{(k-1)} \right)^T \varphi_j^{(k-1)}, a_{1,j} \triangleq \varphi_1^T \varphi_j \\ b_k \triangleq \left(\varphi_k^{(k-1)} \right)^T y, b_1 \triangleq \left(\varphi_1^{(0)} \right)^T y = \varphi_1^T y \end{cases} \quad (4.62)$$

where $j = 1, \dots, S$ and $k = 0, 1, \dots, S$. According to (4.62), the net contribution ΔE_{k+1} of the new model term φ_{k+1} to the cost function when it is included in the model can be expressed by

$$\Delta E_{k+1} = \frac{\left(y^T \varphi_{k+1}^{(k)} \right)^2}{\left(\left(\varphi_{k+1}^{(k)} \right)^T \varphi_{k+1}^{(k)} \right)} = \frac{(b_{k+1}^T)^2}{a_{k+1,k+1}}, k = 0, \dots, S-1 \quad (4.63)$$

By estimating the net contribution of each term using (4.63), the importance of all model terms can be ranked and a total of k model terms with maximum net contributions are selected one by one. After that, the parameters of the k selected model terms can be calculated by

$$\hat{\theta}_j = \frac{b_j - \sum_{i=j+1}^k \hat{\theta}_i a_{j,i}}{a_{j,j}}, j = k, k-1, \dots, 1 \quad (4.64)$$

Notably, $\sum_{i=k+1}^k \hat{\theta}_i a_{k,i} = 0$.

As aforementioned, a deep neural network, as the agent in the DQN algorithm, is used to approximate the action-value Q function. Generally, the adopted deep neural network for the DQN agent has multiple layers and neurons, which results in a large amount of model parameters. It will cost large computation and memory resources so as to limit the implementation of the trained agent in the real energy flow controller. To reduce the complexity of the agent, an FRA-based network pruning method is proposed to reshape the trained agent of DQN by removing the redundant neurons based on the net contributions of all neurons. Meanwhile, based on the proposed FRA-agent pruning

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method, the model parameters (neuron wights) can be re-assigned for the pruned agent to guarantee the accuracy of the approximation of the action-value Q function.

The adopted DNN for the DQN agent in this chapter has four layers, including one input layer, one output layer and two fully-connected (FC) hidden layers. Suppose $X_0 \in \mathbb{R}^{N \times L}$ is the input matrix to the input layer, where N is the number of the samples stored in the replay memory of DQN and L represents the number of the states in each sample, i.e. $L = \text{num}(S)$. For the input layer, the outputs are equal to the inputs, i.e. $Y_0 = X_0$. $X_i \in \mathbb{R}^{N \times (I(i)+1)}$ ($i = 1, 2, 3$) represents the input matrix to the first hidden layer, second hidden layer and output layer. X_i is constituted by the outputs of the previous layer and a $N \times 1$ bias vector with all elements being set to 1, i.e. $X_i = [Y_{i-1} \parallel [1]_{N \times 1}]$. $I(i)$ is the number of the inputs of layer i , which is also equals to the number of neurons of the previous layer, i.e. $I(i) = \text{num}(Y_{i-1})$. $Y_i = [y_{i,1}, y_{i,2}, \dots, y_{i,N}]^T \in \mathbb{R}^{N \times O(i)}$ ($i = 1, 2, 3$) denotes the output matrix from layer i . $O(i)$ is the number of the outputs of layer i . Notably, based on the DQN algorithm, for the output layer, $O(3)$ is equal to the number of actions, i.e. $O(3) = \text{num}(A)$. The neural network model thus can be denoted as

$$\begin{cases} Y_0 = X_0 \\ X_i = [Y_{i-1} \parallel [1]_{N \times 1}] \quad (i = 1, 2, 3) \\ \mathcal{Z}_i = X_i \Theta_i + \Xi_i \quad (i = 1, 2, 3) \\ Y_i = f(\mathcal{Z}_i) \quad (i = 1, 2, 3) \end{cases} \quad (4.65)$$

where $\Theta_i \in \mathbb{R}^{(I(i)+1) \times O(i)}$ represents the parameter matrix of layer i , which consists of the $I(i) \times O(i)$ weight matrix and $1 \times O(i)$ bias vector. $\mathcal{Z}_i$ is an intermediate matrix representing the linear relationship of the inputs. Ξ_i is the residual vector of layer i . $f(\cdot)$ represents the activation function.

To remove the redundant neurons of the trained agent without sacrificing the overall performance, take layer i as an example. The detailed procedure including four steps for the neuron selection and network reshaping is illustrated as follows:

Step 1: Calculate the net contribution of each input in layer i . Suppose $\mathcal{Z}_i = [z_{i,1}, z_{i,2}, \dots, z_{i,N}]^T \in \mathbb{R}^{N \times O(i)}$ is the intermediate matrix of layer i . Based on (4.63), the net contribution of

each input in layer i can be calculated by

$$\Delta E_{k+1} = \frac{\left((\mathcal{Z}_i)^T x_{k+1}^{(k)} \right)^2}{\left(x_{k+1}^{(k)} \right)^T x_{k+1}^{(k)}}, k = 0, 1, \dots, I(i) - 1 \quad (4.66)$$

Notably, the net contribution of each input in layer i also reflects the importance of each neuron of layer $i - 1$. Then rank the inputs based on their net contributions

Step 2: Select the highest-ranked M inputs with M initially being set to 1, and then re-assign the parameters for the selected inputs based on (4.67)

$$\hat{\theta}_{i,j} = \frac{\left(x_j^{(j-1)} \right)^T \mathcal{Z}_i - \sum_{p=j+1}^M \hat{\theta}_p \left(x_j^{(j-1)} \right)^T x_p^{(j-1)}}{\left(x_j^{(j-1)} \right)^T x_j^{(j-1)}}, j = M, M-1, \dots, 1 \quad (4.67)$$

where M is the total number of the selected inputs. Define $\hat{\Theta}_i = [\hat{\theta}_{i,1}, \hat{\theta}_{i,2}, \dots, \hat{\theta}_{i,M}]^T$

Step 3: Evaluate the performance of the reshaped layer i . The outputs of the reshaped layer i can be calculated as

$$\begin{cases} \hat{\mathcal{Z}}_i = \hat{X}_i \hat{\Theta}_i + \Xi_i \\ \hat{Y}_i = f(\hat{\mathcal{Z}}_i) \end{cases} \quad (4.68)$$

The root mean square error between $\hat{Y}_i$ and Y_i over N samples is given as

$$RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^N \left((\hat{y}_{i,n} - y_{i,n}) (\hat{y}_{i,n} - y_{i,n})^T \right)} = \frac{1}{\sqrt{N}} \|\hat{Y}_i - Y_i\| \quad (4.69)$$

where $\|\cdot\|$ is the Euclidean norm.

Step 4: Repeat steps 2-3 until M reaches the maximum number of inputs in layer i with M increased by 1 in each cycle, or the value of RMSE in (4.69) is smaller than the predefined limit.

Based on the Steps 1-4, the flowchart of the FRA-based pruning method for the DQN agent is demonstrated in Figure 4.5.

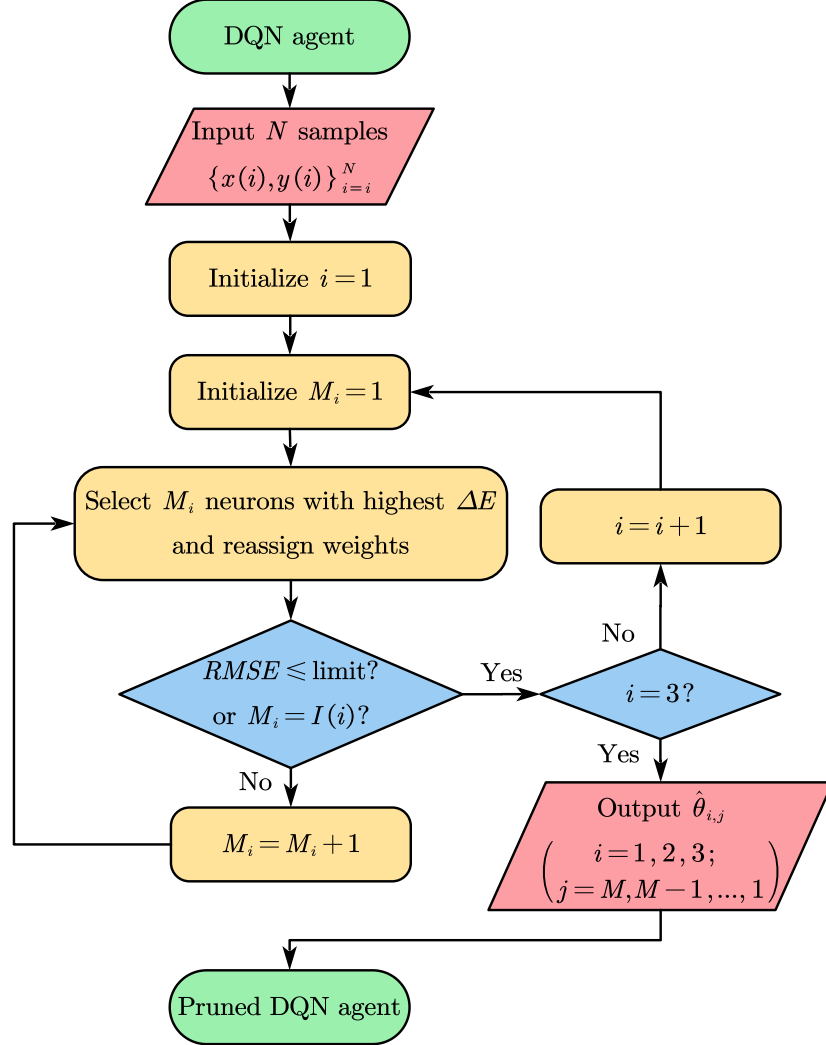


Figure 4.5: Flowchart of FRA-based agent pruning method.

4.4.3 FRA-pruned DQN-Based Thermal Constrained Energy Management

To solve the formulated optimization problem in (4.47) under the DQN-based framework, the models of the thermal-conscious railway co-phase system integrated with ESS are built. With the defined system states, actions and rewards in Section 4.3, the flowchart of the DQN-based thermal constrained energy management is shown in Figure 4.6. The agent is trained by interacting with the environment. With a set of given actions, the transition of the system states can be obtained by the models introduced in Section 4.2.

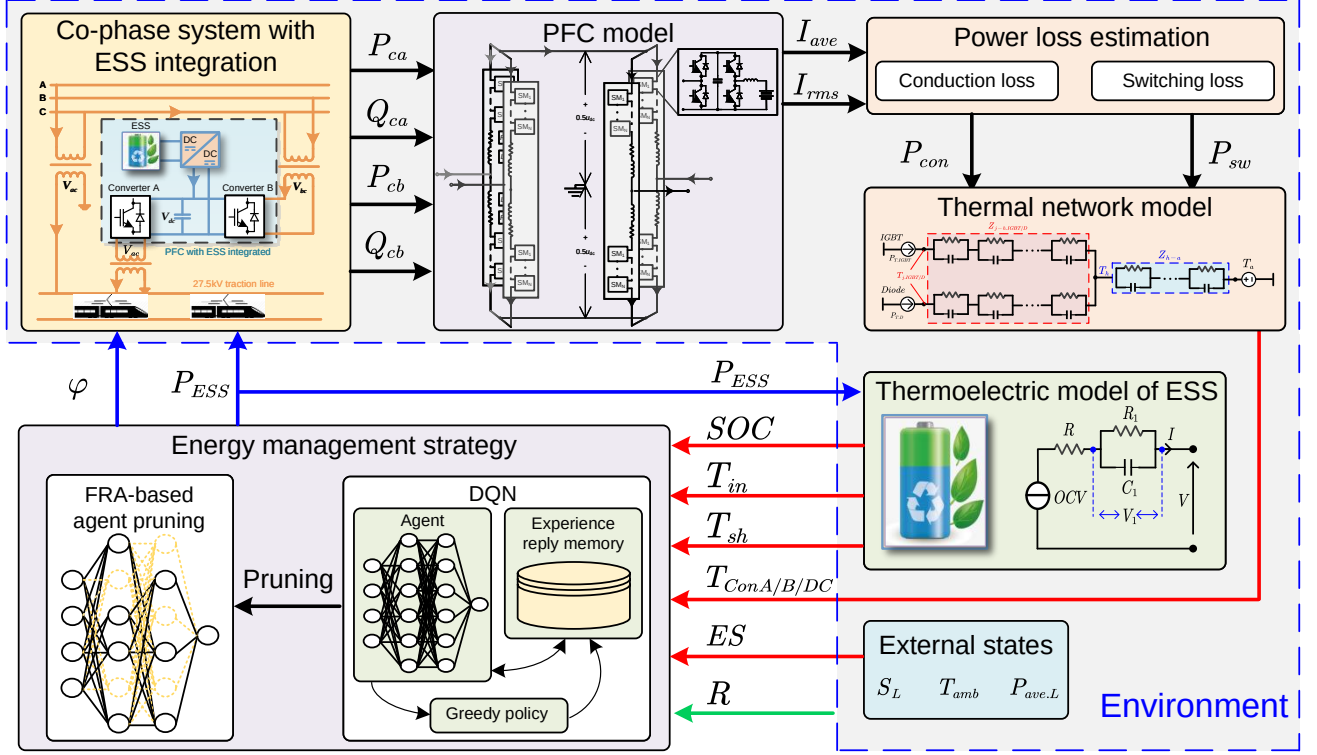


Figure 4.6: Flowchart of FRA-pruned DQN-based thermal constrained energy management strategy.

Meanwhile the reward corresponding to this set of actions is also obtained. With the training process going forward, the agent will gradually converge guided by the reward function. After the training, the proposed FRA-based pruning method is adopted to make the DQN agent more compact. It is worth noting that the DNN parameters of the agent are fixed after pruning. And the pruned agent deployed in the controller can directly give a set of optimal actions for the energy management based on the real-time system states.

4.5 Case studies

In this section, to verify the effectiveness of the proposed FRA-pruned DQN based thermal constrained energy management strategy, comprehensive case studies are performed on a PC with a 2.80GHz Intel i7-7700HQ CPU and 16GB RAM. The algorithm is developed on Python 3.0 and Keras.

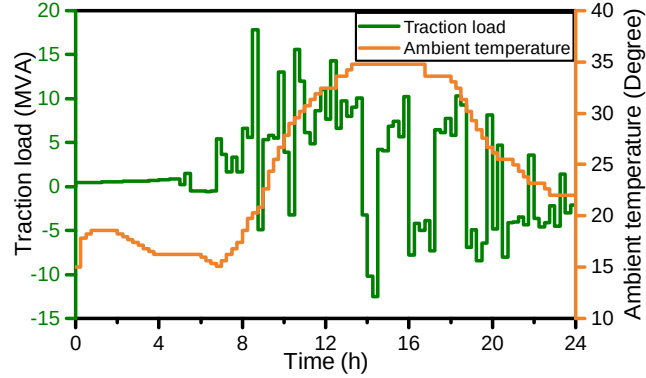


Figure 4.7: Traction loads and ambient temperature.

4.5.1 Case Description and Input Parameters

Taking a high-speed railway station in China as an example, the traction load curve with a sampling time of 15 mins is shown in Figure 4.7 [202], where the positive values represent the power fed into the trains, and the negative ones represent the regenerative power from the braking trains. The whole optimization time is one day including 96 intervals (15 mins per interval). The time period is set to 1 second for the precise system state iteration. The ambient temperatures of the whole day are shown in Figure 4.7.

The management strategy is highly related to the weighting factors selected in (4.47). Generally speaking, a larger weighting factor suggests greater importance of the objective or more stringent compliance to the imposed constraints, while a smaller weighting factor implies less importance of the objectives or softer constraints allowing certain level of violation tolerance of the constraints. The weighting factors are therefore set as the trade-off between different objectives and constraints, and in this chapter, a , b , c and d are set as 5, 1, 10 and 1000, respectively. Among them, the SoC constraint is seen as a hard constraint that has to be strictly observed under any circumstances, thus a rather large value of 1000 is assigned for d . Meanwhile, the temperature is desired to be controlled below a certain value to avoid unexpected degradation or thermal runaway incidents. However, such constraints may be violated in practice due to the uncertainties stemmed from estimation errors and external disturbances. Instead of using a hard constraint, therefore, the temperature constraint is set as a soft constraint allowing

Table 4.1: Parameters of PFC and DC-DC converters

Parameters of PFC	Values	Parameters of DC-DC converter	Values
Number of SMs in each arm	15	Rated voltage of battery side	832 V
Rated voltage of AC side	10 kV	Rated voltage of PFC side	1000 V
Rated DC-link voltage of each SM	1000 V	Maximum current ripple	30%
Switching frequency	1000 Hz	Switching frequency	10 kHz

Table 4.2: Parameters of Power Electronics Modules

Modules			
SKiiP 1213 GB123-2DL V3/ SEMiX 453 GB12E-4p			
Parameters	Values	Parameters	Values
E_{on+off}/mJ	390/ 45	$K_{v.T}$	1.3/ 1.3
E_{rr}/mJ	56/ 30	$K_{v.D}$	0.6/ 0.6
$C_{E.T}$	0.003/ 0.003	I_{ref}/A	600/ 450
$C_{E.D}$	0.006/ 0.006	V_{ref}/V	900/ 600
$K_{i.T}$	1/ 1	$T_{ref}/^\circ\text{C}$	125/ 150
$K_{i.D}$	0.6/ 0.6		

certain level of violation tolerance. The penalty term c is assigned with a relatively large value of 10. Unlike the above constraints, the objectives of peak power shaving and phase angle are not directly linked to the system safety and reliability, and both are considered to be part of the system operation optimization problem. Thus the weighting factors a and b are assigned with a relatively small value of 5 and 1, respectively. The objective of the phase angle is assigned with a less important factor than that of the peak power shaving since the actions for the phase angle have been limited in an allowable range. That implies that even if the phase angle is not considered in (4.47), the phase angle will still satisfy the operation requirement of the power grid. Furthermore, the settings of the weighting factors have already taken into account the dimensional compatibility issue of different objectives. It is also worth noting that the trained agent under a specific set of weighting factors can provide a representative solution of the whole Pareto front in a multi-objective optimization problem, which can well be used to verify the performance of the proposed method.

In the co-phase system, the ESS integrated PFC has 15 SMs in each arm, 120 SMs in total for eight arms. The design parameters of the PFC and DC-DC converters are listed

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in Table 4.1. The SEMIKRON IGBT module SKiiP 1213 GB123-2DL V3 [190] is used for the PFC converters, and SEMIKRON IGBT module SEMiX453 GB12E4p [191] is used for the DC-DC converters. The parameters of the selected power electronics modules are listed in Table 4.2. Based on the datasheets [190, 191], the operation temperature of power electronics modules is normally within the range of -40°C to 85°C . The lifetime will be significantly reduced when the junction temperature is higher than 85°C . Thus the penalty term of the overtemperature for the power electronics modules is triggered from 85°C . For the ESS, a LiFePO₄ Graphite battery is used in this chapter. One battery cell has a capacity of 10Ah and a nominal operating voltage of 3.2V. In order to achieve a total ESS capacity of 5 MWh, it needs to be distributed among the 120 SMs (8 arms, 15 SMs per arm). This means that each arm should have a capacity of 41.7 kWh. To meet the design specification of a DC link voltage of 832V on the battery side, it is necessary to connect 250 branches in series, with 8 battery cells connected in parallel on each branch. Based on [192], the internal resistance will rise noticeably when the SoC falls below 20%, which would lead to a large internal heat generation and speed up the battery degradation. Thus battery is only cycled in the range higher than 20% SoC. Meanwhile, within this range, the battery internal resistance does not change much with SoC variation, and the accuracy of the adopted ESS electrothermal model will then become relatively high as the internal resistance is primarily related to the internal temperature within this SoC range. The parameters of the ESS and the battery cell are listed in Table 4.3. Based on [192], in real applications, the lithium-ion battery would be degraded faster when its internal temperature is greater than 40°C . This has also been confirmed in [172, 179], that the lifespan of the ESS would be reduced quickly when the working temperature is higher than 40°C . Given the aforementioned considerations, the penalty-triggering temperature in the objective function is set to 40°C . Furthermore, the soft constraint for the overtemperature is also set at 40°C . The hyperparameters used in the DQN training are listed in Table 4.4, their settings are experience-based from the literature [172, 179, 186, 198, 203].

To verify the proposed FRA-pruned DQN-based thermal constrained energy manage-

Table 4.3: Parameters of ESS

Parameters	Values	Parameters	Values
Rated capacity of ESS	5 MWh	a_1	0.982
Maximum power of ESS	5 MW	b_1	2.1e-4
Range of SoC	0.2-1.0	c_1	264.7
Rated voltage of battery cell	3.2 V	c_2	30.7
Rated capacity of battery cell	10 Ah	k_1	1.286
		k_2	0.3009
OCV		See [192]	
R		See [192]	

Table 4.4: Hyperparameters for Training the Agent

Parameters	Values	Parameters	Values
No. of hidden layers	2	Total episodes	10000
No. of neurons	80 / 250	Learning rate	0.001
Activation function	ReLU	Minibatch size	64
Experience pool size	20000	Discount factor	0.98

ment, five scenarios are investigated:

1. Rule-based energy management under phase angle $\varphi = 0^\circ$ without ESS integration
2. Rule-based energy management under phase angle $\varphi = 20^\circ$ without ESS integration
3. DQN based thermal constrained energy management without ESS integration
4. DQN based energy management with ESS integration
5. DQN based thermal constrained energy management with ESS integration

The scenarios examined to verify the performance of the proposed DQN-based thermal-constraint energy management strategy cover the optimization of various control objectives for the railway co-phase system integrated with or without the ESS, and the thermal performance of both the power electronics devices and ESS are examined. The first three scenarios presented in Section 4.5.2 consider the railway co-phase system without ESS. The purpose is to verify and compare the performance of the proposed strategy against popular rule-based strategies in reactive power compensation while

satisfying the temperature constraints. While the next two scenarios presented in Section 4.5.3 consider the railway co-phase system integrated with ESS, and the purpose is to verify the performance of the proposed DQN-based thermal-constraint energy management strategy in compensating the reactive power, shaving the peak load while meeting the temperature constraints for both the power electronics modules and ESS. Finally, in Section 4.5.4, the performance of the FRA-based pruning method in reducing the agent complexity is verified.

4.5.2 Performance of DQN-based Strategy for Thermal Management without ESS Integration

In this case, the performance of the DQN-based strategy for thermal management without ESS integration is verified. The PFC is only used to compensate the reactive traction loads. In [204], a full compensation strategy with $\varphi = 0^\circ$ is applied to a 10MVA-rated co-phase system in China. $\varphi = 0^\circ$ implies that the three-phase power grid is fully balanced and all reactive power of the traction loads is compensated by the PFC. This full compensation strategy is adopted first in scenario 1 for the comparison. Under the traction loads as shown in Figure 4.7, the temperatures of converters A and B over the whole day are shown in Figure 4.8 (a). The maximum temperatures of converters A and B are 113.7°C and 89.9°C respectively. Besides, another partial compensation strategy discussed in [63] is also applied in scenario 2 for the comparison purpose. The phase angle is set to $\varphi = 20^\circ$ since $\varphi = 20^\circ$ is the maximum allowable phase angle for the three-phase power grid. The temperatures of converters A and B are shown in Figure 4.8(b). The maximum temperatures of both converters are 74.8°C and 92.5°C respectively.

When the DQN-based thermal management strategy is adopted in scenario 3, the temperatures of converters A and B at different time instants are shown in Figure 4.8 (c). The maximum temperatures of converters A and B are 85.9°C and 91.5°C respectively. Considering both converters A and B, the maximum temperatures under the rule-based energy management strategies with $\varphi = 0^\circ$, $\varphi = 20^\circ$ and under the DQN-based strategy all exceed the limit by 28.7°C , 7.5°C , and 6.5°C respectively. While it is clear that DQN-

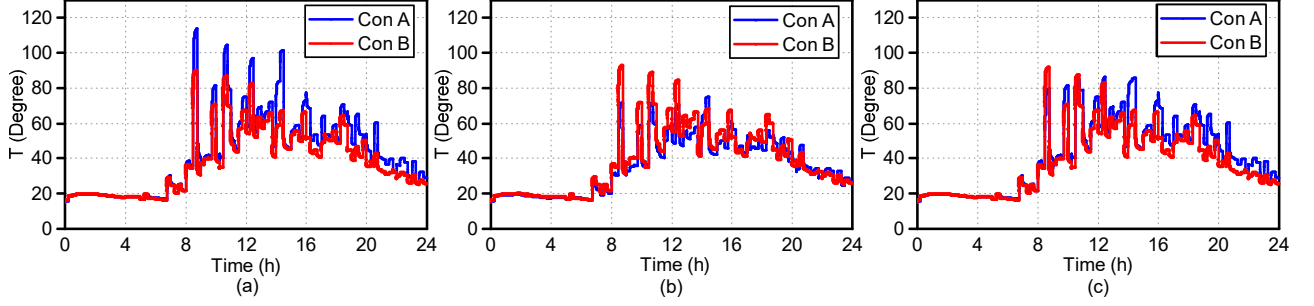


Figure 4.8: Thermal performance comparisons of converters without ESS integration. (a) S1; (b) S2; (c) S3 DQN-based strategy.

based strategy performs better for constraining the thermal performance. To further verify the performance of the proposed DQN-based thermal management strategy, an index reflecting the cumulative values of temperature exceeding the limit is defined as:

$$CT(k) = \sum_0^k \rho_{T(\cdot)}(k) \quad (4.70)$$

where the definition of $\rho_{T(\cdot)}(k)$ has been given in (4.45). $CT(k)$ of converters A and B over the whole day is shown in Figure 4.9, where $CT(k)$ of PFC is defined as the sum of $\rho_{T(\cdot)}(k)$ of converters A and B at each time instant. It can be seen that, at the final time instant of the whole day, $CT(k)$ of PFC based on the proposed DQN-based strategy is the smallest, which is shown as the solid blue line in Figure 4.9. The partial compensation strategy with $\varphi = 20^\circ$ has a similar but slightly larger $CT(k)$ value (solid green line) than the proposed strategy. The full compensation strategy with $\varphi = 0^\circ$ has the largest $CT(k)$ value (solid red line). It implies that, over the whole day, the temperatures of the PFC are overall below the limit under the DQN-based strategy. Even if the temperatures exceed the limit at some specific time instants, they do not stretch the limit significantly and the undesirable temperature condition does not last long either. The details of $CT(k)$ at the final time instant under different strategies are listed in Table 4.5. It is evident that the proposed DQN-based strategy outperforms the fixed rule-based full and partial compensation strategies in terms of the temperature limit, and a reduction of 89.3% in the CT values, i.e. the total temperature violation against limits, under Scenario 3 can be achieved by the proposed DQN-based strategy compared to the full compensation

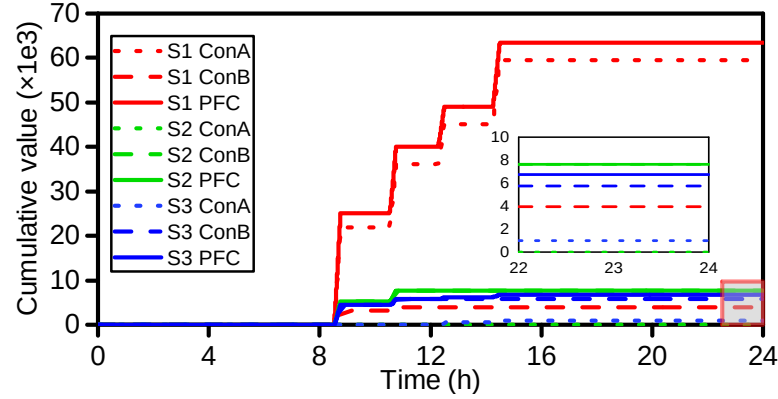


Figure 4.9: $CT(k)$ of S1, S2 and S3.

strategy (Scenario 1).

It is worth noting that in this case, the thermal management is achieved by optimising the phase angle φ of the three-phase power grid. In Scenario 3, under the proposed energy management strategy, the phase angles are kept at 0° for most of the time, except for 16° , 12° , 8° and 12° at the 35th, 43rd, 50th and 58th time intervals. These four time intervals are exactly the periods when the temperature exceeds the boundary in Scenario 1 which does not consider the temperature constraint. The trained DQN agent is able to respond quickly during the intervals when the temperature constraints are violated to constrain the temperature increase by adjusting the phase angles. Thus the phase angles do not change violently. When φ is not equal to zero, some reactive power will be injected into the three-phase power grid. The cumulative reactive energy (CRE) injected into the three-phase power grid during the whole day under different strategies are listed in Table 4.5. It is obvious that the reactive power remains zero under the full compensation strategy. While the thermal performance under this strategy is undesirable and even not acceptable. Under the partial compensation strategy with $\varphi = 20^\circ$, the total reactive energy reaches 40.1MVarh during the whole day with the equivalent reactive power (ERP) of 1.7MVar. Under the DQN-based strategy, the total reactive energy is only 3.6MVarh with a reduction of 36.5MVarh compared to the partial compensation scheme and a relatively small average equivalent reactive power of 0.15MVar is required for the railway power supply. The amount of reactive power under $\varphi = 20^\circ$ is seen as the

maximum allowable reactive power injected to the three phase power grid. Under the proposed DQN-based energy management, the injected reactive power only accounts for 9.0% of the maximum allowable amount. In summary, the proposed DQN-based strategy can not only manage the thermal performance effectively but also reduce the reactive power injected into the three-phase power grid as much as possible.

4.5.3 Performance of DQN-based Strategy for Peak Load

Shaving and Thermal Management with ESS Integration

In this case, the ESS is integrated into the co-phase system to achieve a more flexible power flow. Two different strategies are applied in this case. Both strategies aim to shave the peak traction power as well as compensate the reactive power by using the DQN-based strategies, but one considers thermal management (Scenario 5) and the other does not (Scenario 4). Figure 4.10 (a) shows the required power from the three-phase power grid under both strategies. It is evident that, compared to the original traction power, the maximum required power under both strategies is significantly reduced from 16.9MW to 13.6MW with a 19.5% reduction whether the thermal management is considered or not. The maximum regenerative power is reduced from 11.9MW to 6.9MW with a reduction of 42.0% when the thermal management is not considered, and to 8.1MW with a reduction of 31.9% when considering thermal management. Figure 4.10 (b) shows the actions and corresponding SoC of the ESS. The actions of the ESS determined by the strategies without/ with considering thermal management are denoted by the blue and red bars respectively. The bars with positive values represent the discharging actions and the bars with negative values represent the charging actions. It can be seen that the trends of SoC under both strategies are similar. When the SoC and traction power are relatively high, the ESS tends to discharge to shave the peak power. When the SoC is relatively low and regenerative power is high, the ESS is operated in the charging mode to shave the peak regenerative power and also absorb energy for the further peak traction load shaving. While for the strategy taking into account the thermal management, the change of the SoC is much smoother than that without thermal management due to the temperature

CHAPTER 4. THERMAL CONSTRAINED ENERGY OPTIMIZATION OF RAILWAY CO-PHASE SYSTEMS WITH ESS INTEGRATION - AN FRA-PRUNED DQN APPROACH

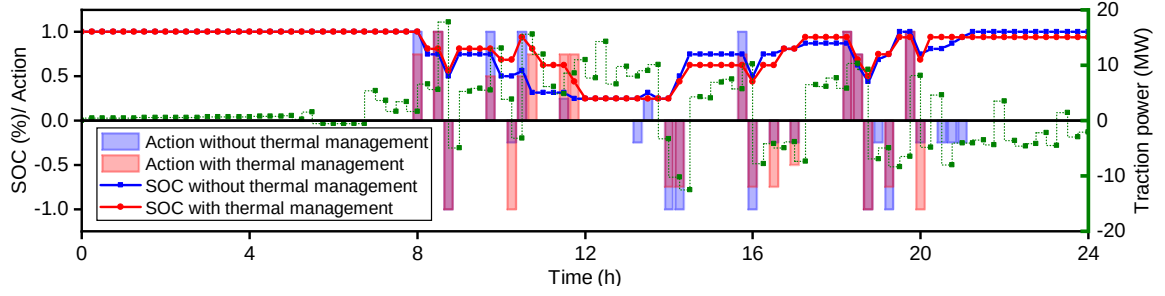


Figure 4.10: Result comparisons. (a) Performance comparisons of load shaving; (b) Comparisons of SoC and actions of ESS.

limitations for the ESS and PFC.

To further demonstrate the effectiveness of the DQN-based strategy for the peak load shaving, a statistical index ΔP given in (4.42) reflecting the absolute difference between the average traction power and required power from the three-phase power grid is shown in Figure 4.11. The smaller values of ΔP means that the three-phase power curve is smoother. As shown in Figure 4.11, the values of ΔP at different time instants over the whole day (86400 time instants in total) are sorted from the largest to smallest. The values of ΔP under both strategies whether considering or not considering thermal management are overall lower than that of the original traction loads. The performance of both strategies for load shaving is similar according to Figure 4.11. Also, the same conclusion can be drawn from Table 4.6 since the average difference of ΔP under both strategies is almost similar, i.e. 3.4MW for Scenario 4 and 3.3MW for Scenario 5 respectively. The details for the peak load shaving under both strategies are listed in Table 4.6. Even if considering the temperature constraints, the DQN-based energy management strategy can achieve a maximum peak load reduction of 31.9% compared to the original traction loads.

Further, the thermal management performance under both strategies is also analysed. As shown in Figure 4.12, with the thermal management, the temperature of ESS is lower than the limit during the whole day. While the maximum temperature of ESS under the strategy without thermal management exceeds the limit, reaching 44.6 °C. For the PFC, compared to the strategy without thermal management, the proposed strategy with thermal consideration performs better in terms of the thermal management. As

Table 4.5: Comparisons of Thermal Management and Reactive Power Compensation

	CT (1e3)				CRE	ERP
	Con A	Con B	PFC	ESS	(MVarh)	(MVar)
S1	59.6	4.0	63.6	/	0	0
S2	0	7.6	7.6 (88.1% ↓)	/	40.1	1.67
S3	1.0	5.8	6.8 (89.3% ↓)	/	3.6	0.15
S4	93.7	0	93.7	7.2	0	0
S5	5.5	0	5.5 (94.1% ↓)	0 (100% ↓)	3.4	0.14

shown in Figure 4.13, the maximum temperatures of converter A under two strategies with and without thermal management are 89.6°C and 124.1°C respectively. The index $CT(k)$ of converter A at the final time instant is listed in Table 4.5. A temperature reduction of 94.1% can be achieved under thermal-constrained strategy (Scenario 5) compared to the strategy without considering the temperature constraint (Scenario 4). The temperatures of converter B and DC-DC converter are below the limit across the whole day under both strategies. Besides, the proposed DQN-based strategy with thermal management only injects 3.4MVarh reactive energy, equivalent to 0.14MVar reactive power which is acceptable for the railway power supply system. Overall, the proposed thermal constrained DQN-based strategy not only performs well in load shaving, the thermal performance is also much better than the strategy without considering the temperature constraint.

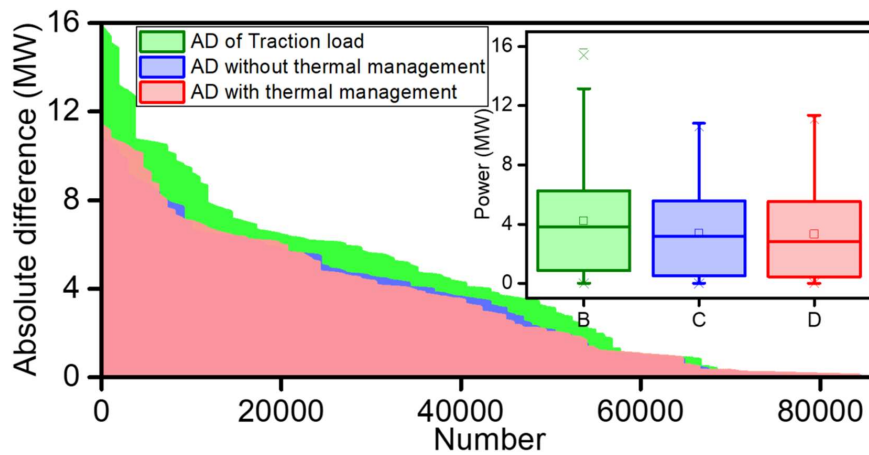


Figure 4.11: Comparisons of absolute difference under different strategies.

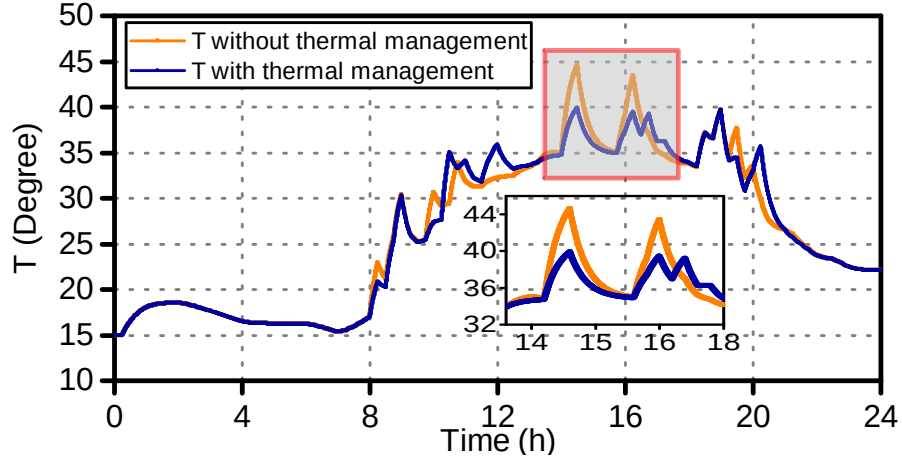


Figure 4.12: Thermal performance comparisons of ESS.

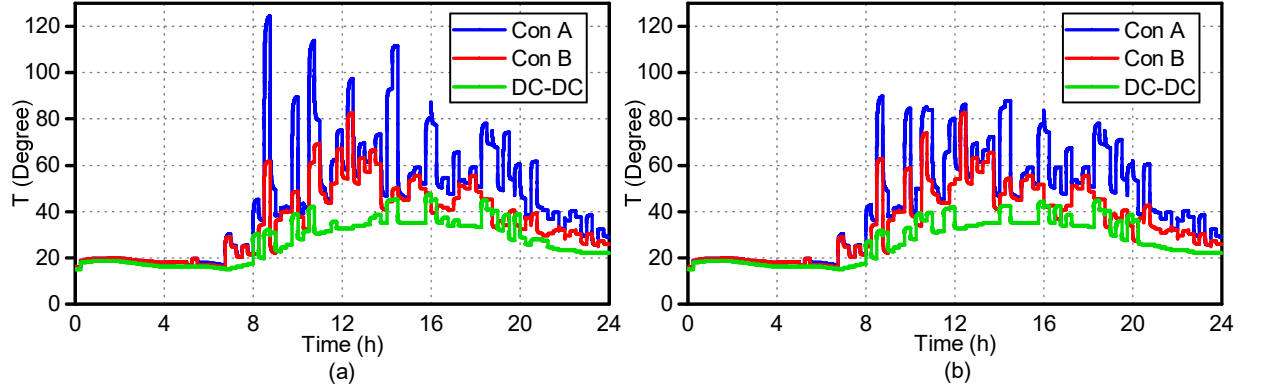


Figure 4.13: Thermal performance comparisons of converters. (a) S4 without thermal management; (b) S5 with thermal management.

Table 4.6: Comparisons of Peak Load Shaving

	Max required power	Max regenerative power	Average difference
Traction load	16.9 MW	11.9 MW	4.2 MW
DQN without thermal management	13.6 MW	6.9 MW	3.4 MW
DQN with thermal management	13.6 MW	8.1 MW	3.3 MW
	(19.5% ↓)	(42.0% ↓)	(19.1% ↓)
	(19.5% ↓)	(31.9% ↓)	(21.4% ↓)

4.5.4 Performance of Training Process and FRA-based Pruning for Complexity Reduction

To further verify the superiority of the adopted prioritized DQN algorithm and FRA-based pruning method, comparative studies are conducted. Firstly, as aforementioned,

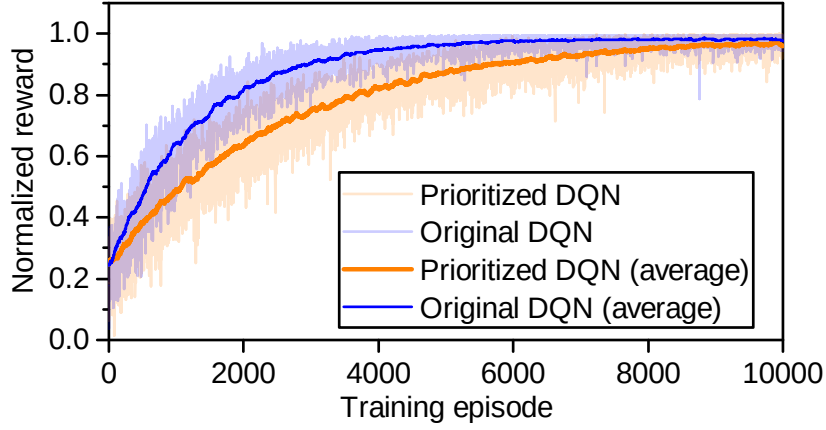


Figure 4.14: Performance comparisons of training process.

the prioritized DQN algorithm is adopted during the agent training for fast convergence. Compared to the original DQN proposed in [127], the convergent speed of the prioritized DQN algorithm is theoretically faster. To verify this, the training performance of the original DQN algorithm and the prioritized DQN algorithm used in Scenario 5 are compared in Figure 4.14, where the rewards are normalized. In Figure 4.14, the solid blue line and orange line represent the average normalized rewards of the prioritized DQN and original DQN per 100 episodes. It can be seen that, as expected, the training performance of the prioritized DQN is better than that of the original DQN since the prioritized DQN makes the training converge faster and has the slightly higher overall rewards.

In Section 4.4.2, the FRA-based DQN pruning method is proposed to reshape the DNN-based agent to make the agent more compact and reduce the computational complexity. The pruning process is only used for the fully connected layers. In this chapter, before the training, the agent is designed as a neural network with two hidden layers. The first hidden layer includes 80 neurons and the second one includes 250 neurons. After training, the FRA-based pruning method is applied and the pruning process is performed based on Steps 1-4 in Section 4.4.2. The final RMSE of the loss is set to be lower than 0.2, which has been verified that the pruned agents will be guaranteed to perform the same actions as before. In the case studies, the DQN-based energy management is adopted in Scenarios 3, 4 and 5 respectively. Table 4.7 shows the

Table 4.7: Performance of FRA Pruning

		1st FC layer		2nd FC layer		Model size (KB)	Parameters
		Number of neurons	FLOPs	Number of neurons	FLOPs		
S3	Original	80	800	250	40,000	567	45,579
	Pruned	39	390	66	5,140	57	9,507
	Reduction	51.3%	51.3%	73.6%	87.2%	89.9%	79.1%
S4	Original	80	640	250	40,000	560	45,499
	Pruned	40	320	114	9,120	80	16,259
	Reduction	50.0%	50.0%	54.4%	77.2%	85.7%	64.3%
S5	Original	80	1,440	250	40,000	567	45,899
	Pruned	52	930	144	14,976	106	22,507
	Reduction	35.0%	35.4%	42.4%	62.6%	81.3%	51.0%

performance of the FRA-based pruning method for the trained agents in Scenarios 3, 4 and 5. The floating point operation (FLOPs) are considered to evaluate the computational cost. From Table 4.7, after pruning, the neuron numbers of both hidden layers of the three reshaped agents are significantly decreased compared to these of the original agents before pruning, with a maximum reduction of 73.6%. Accordingly, the FLOPs of both layers are also decreased and the maximum reduction is up to 87.2%. Compared to the original agents, the total parameters of the three reshaped agents are also decreased with reductions ranging from 51.7% to 79.2%. It is worth noting that the model sizes of the reshaped agents are also significantly reduced with the reductions of all three reshaped agents being more than 80.0% and a maximum reduction of 89.9%. The FRA-based agent pruning method not only makes the decision process faster, but also saves more memory resources for the controller. These benefits from the FRA-based pruning method are meaningful for the real application of the proposed DQN-based energy management.

4.6 Conclusions

This chapter has proposed a DQN-based thermal constrained energy management strategy for the railway co-phase system integrated with ESS. To constrain the thermal dynamics for both the power electronics modules and ESS and enhance their reliability,

the overtemperature penalty terms are introduced in the problem formulation, and the DQN-based method is adopted to achieve the reactive compensation and peak traction load smoothing with the aid of the ESS. An FRA-based pruning method is then proposed to make the agent more compact without sacrificing the performance. Case studies are conducted to verify the effectiveness of the proposed method. The major conclusions are drawn as follows:

1. Without ESS integration, the proposed DQN-based energy management strategy for the temperature constraint outperforms the rule based strategies with the maximum temperature reductions of 89.3%. Meanwhile, the reactive power can be compensated as much as possible with the injected reactive power accounting for 9.0% of the maximum allowable amount.
2. With ESS integration, both DQN-based energy management strategies with or without considering temperature constraints can achieve the peak load shaving with maximum reductions of 31.9% and 42.2% respectively. Compared to the strategy without considering temperature constraints, the strategy considering temperature constraints can achieve a temperature reduction of 94.1% for power electronics modules and 100% for the ESS.
3. The FRA-based agent pruning method can achieve a maximum parameter reduction of 79.1% and a maximum agent size reduction of 89.9% without sacrificing the performance compared to original agents before pruning.

Finally, it needs to be pointed out that in practical applications, the operation of the railway co-phase power supply system is often subject to many uncertainties and stochasticity, and their impacts on the performance of the proposed DQN-based energy management strategy still deserve further studies. For example, forecasting techniques to capture the system stochasticity rooted in the uncertain traction demand and system parameter deviations need to be considered and incorporated into the proposed thermal-constraint energy management strategy.

CHAPTER 4. THERMAL CONSTRAINED ENERGY OPTIMIZATION OF RAILWAY CO-PHASE SYSTEMS WITH ESS INTEGRATION - AN FRA-PRUNED DQN APPROACH

From the railway power supply side, Chapters 3 and 4 have investigated the optimal operation of the railway cophase system with integration of renewable generations and ESS. However, to maximize the energy efficiency of the railway system, from the train operation side, the train trajectory optimization is another important issue to be addressed, leading to the next chapter.

ROBUST OPTIMIZATION OF ENERGY-SAVING TRAIN TRAJECTORIES UNDER PASSENGER LOAD UNCERTAINTY BASED ON P-NSGA-II

To improve the energy efficiency of train operations, of particular interest is the optimization of train speed trajectories. However, most studies formulate the problem as a single-objective optimization model and do not take into account train mass uncertainty associated with the passenger load variations. This chapter formulates a bi-objective robust optimization model to minimize both the energy consumption and journey time, in which the robustness against the uncertain train mass is considered and viewed as a decision-maker preference. A novel multi-objective optimization algorithm namely p-NSGA-II is proposed, incorporating the original NSGA-II and a proposed preference dominance criterion to handle the DM preference. With the proposed p-NSGA-II, not only all solutions will converge to the optimal Pareto front but also solutions with better robustness in the Pareto front will be automatically selected and retained, meanwhile the spread of the selected solutions is maintained. The effectiveness of the p-NSGA-II to generate a set of performance-robust driving schemes is verified by numerical case studies. The results show that the p-NSGA-II can achieve up to 40.59% robustness

improvement compared to the original NSGA-II.

5.1 Introduction

High-frequency, high-density train schedules often lead to dramatically increased energy consumption from the train operation side which is becoming a major concern for railway companies. Many measures have been taken to reduce energy consumption, such as rescheduling of operating timetables [205–209], installation of energy storage systems [135, 140, 141, 210–213], and reducing vehicle resistance. Among these, optimization of the train speed trajectory is seen as an effective and economical approach that requires no no additional investment in infrastructure and equipment. It is also the most cost-effective approach to address the uncertainties at the train planning and operation stage for given timetable and power supply capacity.

Much effort so far has been put into developing energy-saving operating schemes for trains. In earlier work, the optimization of the train speed trajectory is usually formulated as a mixed-integer linear programming (MILP) problem for minimum energy consumption [141, 214–216], while some approximations using linearization are required. With later advances in computer performance, more studies were focused on developing meta-heuristic algorithm based optimization models [143, 217–223]. In [224, 225], multiple-phase trajectory controls are proposed and additional practical factors have been incorporated in the optimization models, such as passenger comfort and punctuality. In summary, studies on single-objective optimization of a train speed trajectory are mature.

However, single-objective optimization may suffer from a few limitations and fail to meet the requirements where multiple conflicting objectives exist simultaneously. In a modern railway system, an automatic train operation (ATO) system is widely deployed to achieve energy-saving driving [226, 227], and several popular driving patterns have been proposed, such as the cruising pattern and coasting-remotoring pattern [228–230]. Generally speaking, the driving trajectories need to be pre-programmed into the ATO

system based on the required arrival time. Thus, to meet different requirements on the journey time (timetable), it is preferred to provide in advance a set of driving profiles with different arrival time, rather than only one option. However, single-objective optimization can only produce a single solution rather than a comprehensive set of solutions. To tackle this drawback, the train speed trajectory optimization has been formulated as a bi-objective problem, where the objectives include energy consumption and running time. In this way, a set of Pareto-optimal driving schemes characterized by various arrival times can be produced. For example, a bi-objective speed trajectory optimization model is proposed in [231]. A multi-objective particle swarm optimization (MOPSO) is developed and applied to obtain a set of Pareto-optimal speed profiles. This type of bi-objective optimization model is also adopted in [232], [233] and [230]. The bi-objective optimization models minimizing both the energy consumption and journey time can effectively handle the speed trajectory planning problem, fit well the existing onboard ATO system and meet various operational requirements.

In the aforementioned studies, the optimization problems are formulated as deterministic models and related parameters are assumed to be constant. In reality, operation of a railway system is usually affected by uncertain factors which may greatly disturb the operation or even lead to worse consequences. In the context of engineering applications, various methods have been proposed to handle the uncertainties to mitigate their impacts [234–236]. However, few studies on railway operation optimization have considered the uncertainties. [137] considers the uncertainty in traction force and train resistance. The optimization for the speed trajectory was formulated as a Markov decision process and solved by an approximate dynamic programming (ADP) based method. However, the train mass, as a significant source of uncertainties, was not considered. So far, the train mass uncertainty associated with complex passenger distributions is still seen as the greatest challenge for a speed trajectory optimization. As pointed out in [230, 237], the maximum passenger mass is around 30% of the total train mass which can result in up to 35% energy increment and 8% running time increment. Therefore it is vital to investigate the robustness enhancement to mitigate the negative effects of the random

passenger load. In [238], the authors adopted a method combining an expert system and reinforcement learning to handle the railway system uncertainties such as delays. While it needs a vast amount of operational data to develop the expert rules. In [237], a stochastic programming model for metro timetable rescheduling to reduce the time delay caused by the passenger number uncertainty is developed. However the speed trajectory itself is not optimized. In [239], a two-phase stochastic programming model integrating timetable and speed profile optimization is formulated, considering the train mass uncertainty. However, the stochastic optimization model requires prior information which may result in a high computational cost for the information sampling. Meanwhile, in these studies, the optimization problems are formulated as single-objective programming models which do not meet the requirements of ATO system.

As discussed earlier, several factors, such as energy consumption, journey time and robustness which are affected by the uncertainty of the passenger load, need to be considered simultaneously in the train speed trajectory optimization. Meanwhile, most real-life multi-objective problems suffer from having a large solution space, which may result in a slow and time-consuming optimization process, even non-convergence may occur. One of the measures is to incorporate decision maker's (DM) preferences into the optimization process to reduce the solution space. For example, in [240], a new DM preference-based multi-objective evolutionary optimization algorithm (MOEA) utilizing configured weight intervals is proposed for the ship weather routing. In [241], a novel MOEA incorporating the weight aggregation strategy as the priori DM's preference, is developed to optimize the load scheduling of electric vehicles. In [242], a scoring and dynamic hierarchy-based NSGA-II is designed for workflow scheduling, where a scoring criterion is considered as the DM preference. Besides, [243–248] also introduce some DM preference-based MOEAs. However, these methods are developed for specific problems and not suitable for train speed trajectory optimization problem elaborated earlier. In [230], the speed profile optimization is formulated as a bi-objective optimization problem and optimized by MOPSO. The trainload variations are considered in formulating the optimization constraints which can be viewed as using the DM preference to guide the

search. However, the formulated optimization model involves a pre-defined sensitivity parameter that needs to be set in advance which will significantly affect the final results. Further, the adopted method in [230] may distort the distribution of the optimal Pareto front. Finally, the cruising operation is not considered in the driving patterns, which may lead to suboptimal and less energy-efficient solutions.

This chapter aims to address the aforementioned challenges and to develop robust energy-saving speed profiles considering the uncertainty of train mass. The main contributions are summarized as follows:

1) A bi-objective train speed trajectory optimization problem is formulated where the robustness affected by the uncertain train mass is considered. The robustness of each driving scheme is formulated as the maximum variations of running time and energy consumption due to uncertain passenger loads.

2) To derive a set of optimal driving schemes suitable for a realistic train journey, a train movement control model is adopted which divides the whole journey into multiple subsections based on different speed limits and track gradients. The speed trajectory of each subsection is optimized separately, which helps to explore the flexibility and superiority of different combinations of train operations.

3) A new DM preference-based multi-objective algorithm, namely p-NSGA-II, is proposed. The p-NSGA-II can automatically guide the search to the optimal Pareto front and further to the region of interest (ROI) based on DM preference. Meanwhile, the distribution of the obtained optimal Pareto front can be maintained.

4) The robustness of the train speed trajectories is modeled as the DM preference. By adopting p-NSGA-II, a set of driving schemes, which optimize both energy consumption and journey time, are produced with better robustness. The effectiveness of the formulated optimization model and p-NSGA-II is verified based on extensive case studies.

The remainder of the chapter is organized as follows. Section 5.2 develops the bi-objective optimization model considering the uncertainty of train mass. In Section 5.3, the new DM preference-based algorithm p-NSGA-II is proposed and its implementation procedures are detailed. In Section 5.4, the effectiveness of the p-NSGA-II based robust

optimization of the speed trajectory is verified through two case studies. The performance of the proposed p-NSGA-II is compared with other algorithms including the original NSGA-II and a robust multi-objective optimization method. Finally, Section 5.5 concludes the chapter.

5.2 Model Formulation

5.2.1 Train Kinetic Model

Based on the fundamental Newtonian equations of train motion, the train kinetic model can be described as (5.1), known as Lomonossoff's equation [233], which has been verified in earlier research.

$$\begin{cases} Ma = F - R_1 - R_2 \\ a = \frac{dv}{dt} \end{cases} \quad (5.1)$$

where the train mass M , in unit of kg, consists of the empty vehicle mass M_v and uncertain mass of passengers M_p , i.e. $M = M_v + M_p$. The vehicle mass is seen as a deterministic parameter. While the passengers mass is random at different stations and during different operational periods. a is the train's acceleration rate in unit of m/s^2 . F represents the tractive force or braking force in unit of kN. R_1 and R_2 are the basic resistance and additional resistance of the train respectively, as will be detailed shortly. v is the train velocity in unit of m/s.

In Figure 5.1, the black line shows the motor characteristic curve of the British rail Class 390, a typical electric high-speed passenger train [249]. Whether the train is in the state of traction or braking, it is always governed by this characteristic curve. The whole curve can be split into two regions, with constant torque region or constant power. When the train speed is lower than v_t , the train is operated in the constant torque region, and at higher speed runs in the constant power region. A piece-wise function (5.2) can

represent the motor characteristic curve.

$$F = \begin{cases} uF_{\max} & 0 < v \leq v_t \\ u \frac{P_{\max}}{v} & v_t < v \leq v_{\max} \end{cases} \quad (5.2)$$

where $F_{\max}$ represents the maximum traction/braking force. $P_{\max}$ is the rated motor power. $u \in [-1, 1]$ controls the train's operation command. F is the tractive force when u is positive, and braking force when u is negative.

5.2.1.1 Basic Resistance

The running train is resisted by the track friction and air force. Based on the Davis equation [233], this kind of resistance can be expressed as (5.3), containing the empirical coefficients α , β and γ , the train mass M and speed v . r_1 represents per unit basic resistance. The basic resistance will not exceed the traction force. The curves of basic resistance versus train velocity are also shown in Figure 5.1, for both empty-vehicle and full-load conditions.

$$R_1(v) = r_1(v)Mg = (\alpha + \beta v + \gamma v^2)Mg \quad (5.3)$$

5.2.1.2 Additional Resistance

The additional resistance depends on the track geography and is mainly composed of ramp resistance, curve resistance and tunnel resistance. In most research, only ramp

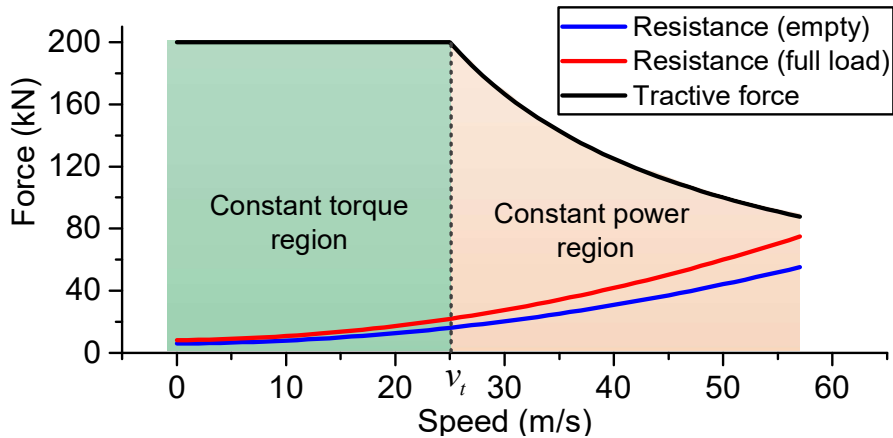


Figure 5.1: Operation characteristic of British rail Class 390.

resistance is considered in (5.4) since it dominates the additional resistance.

$$R_2 = Mg \sin(\theta) \quad (5.4)$$

where θ represents the ramp angle. In addition, the train movement can be expressed as:

$$s(t) = \int_0^t v(t) dt \quad (5.5)$$

where s is the running distance of the train.

5.2.2 Train Driving Pattern and Speed Trajectory Control

In order to construct the optimal and practically feasible train speed trajectories, a method introduced in [232] is adopted. The whole journey between two consecutive stations is divided into n subsections labelled as S1, S2,..., based on different speed limitations as shown in Figure 5.2. For each subsection, several popular driving patterns have been proposed in the literature, such as the cruising pattern and coasting-remotoring pattern [228–230]. In particular, one driving strategy, which considers all possible operations including acceleration, cruising, coasting and braking, has been comprehensively adopted in the ATO system [206, 220, 232, 233], and it helps to explore the flexibility and superiority of different combinations of train operations. As stated in [225, 233], based on Pontryagin’s maximum principle (PMP), if the train is aimed to reach the destination as quickly as possible, the train is supposed to reach the maximum allowable speed first

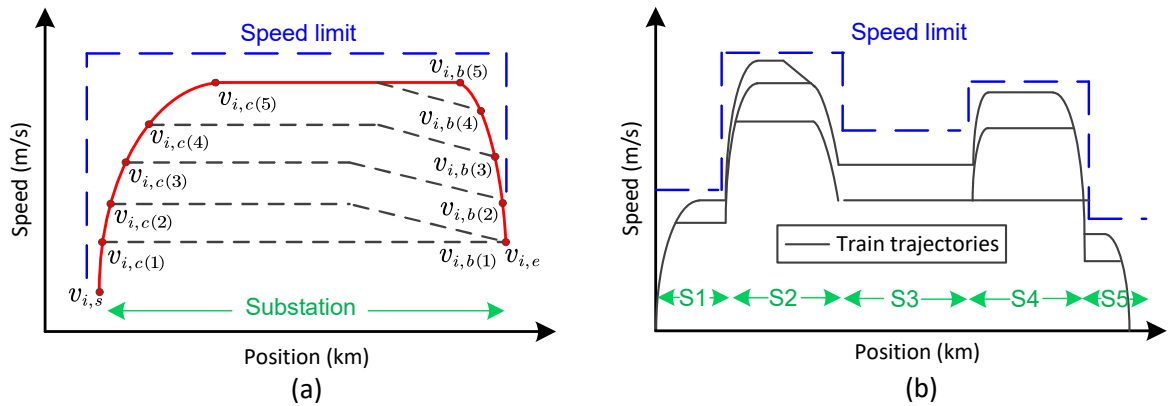


Figure 5.2: Train Speed trajectory control. (a) Speed trajectory control of subsection; (b) Speed trajectories control of whole journey.

with full acceleration and keep the maximum speed (cruising) until the final braking point. Then the full braking is performed to stop the train. More energy-saving driving schemes can be achieved if considering coasting operation and reducing cruising speed. In the following, the combinations of four operations including full acceleration, cruising, coasting and full braking are considered and the driving pattern is introduced. As shown in Figure 5.2(a), in a specific subsection i of the whole journey, four control variables $(v_{i,s}, v_{i,c}, v_{i,b}, v_{i,e})$ are defined to determine a specific sectional speed trajectory. $v_{i,s}$, $v_{i,c}$, $v_{i,b}$ and $v_{i,e}$ represent the start speed, cruising speed, braking speed and end speed of the subsection i respectively. In Figure 5.2 (a), $v_{i,c(1)}, \dots, v_{i,c(5)}$ are the possible candidate choices for the cruising speed, and $v_{i,b(1)}, \dots, v_{i,b(5)}$ are the possible candidate choices for the braking speed. The speed trajectory of each subsection can be depicted as: if $v_c > v_s$, the train is operated in full acceleration mode until the train reaches to the cruising speed v_c and then the cruising operation follows. If $v_c = v_s$, the train is operated in the cruising mode directly. The cruising time depends on the running distance of each subsection. After cruising, the coasting operation follows immediately until the train reaches the set braking speed if $v_b > v_e$. Finally, the train brakes with maximum braking force ($u = -1$ in (5.2)) until the train reaches the end speed at the end point of the subsection. If $v_b = v_e$, the train is operated in the coasting mode until it reaches the end speed of the subsection. Theoretically, based on the above description, once the values for v_s , v_c , v_b and v_e are chosen in advance, the positions of cruising, coasting and braking points can be calculated, and the speed trajectory of each subsection can be plotted, the credibility of which has been verified in [230, 232, 233]. Due to the operational constraints, some rules need to be clarified as follows:

- 1) All the values of v_s , v_c , v_b and v_e should be lower than the speed limit in each subsection.
- 2) $v_c < v_s$ and $v_b < v_e$ are disabled.
- 3) For two successive subsections, the end speed of the former subsection should be equal to the start speed of the later subsection, i.e. $v_{i,e} = v_{i+1,s}$.

For the whole journey including n subsections, the control variables can be expressed

as: $V = (v_{1,s}, v_{1,c}, v_{1,b}, v_{1,e}, \dots, v_{i,s}, \dots, v_{i,e}, \dots, v_{n,s}, v_{n,c}, v_{n,b}, v_{n,e})$ where $v_{1,s} = v_{n,e} = 0$ means the initial and final speeds of the journey are equal to zero. Thus there are $3n - 1$ control variables in total which need to be optimized to form the whole train speed trajectory as shown in Figure 5.2 (b).

5.2.3 Robust Optimization Model of Train speed Trajectory

5.2.3.1 Original Train Speed Trajectory Optimization Model without Considering Robustness

As discussed above, once the set of speed control variables V is confirmed, the whole speed trajectory can be formulated for a specific train mass. The associated total energy consumption and running time can be expressed as (5.6) and (5.7) respectively.

$$E = f_1(V, M) = \sum_{i=1}^n \left(\int_0^{T_i} \max\{0, F(t)\} v(t) dt - \eta \int_0^{T_i} \min\{F(t), 0\} v(t) dt \right) \quad (5.6)$$

$$T = f_2(V, M) = \sum_{i=1}^n (t_{i,a} + t_{i,cr} + t_{i,co} + t_{i,b}) \quad (5.7)$$

where $t_{i,a}$, $t_{i,cr}$, $t_{i,co}$ and $t_{i,b}$ represent the durations of the motoring, cruising, coasting and braking of each subsection. η represents the energy efficiency of the regenerative braking. Generally speaking, the energy consumption and running time also vary with different driving schemes, even for the same journey distance. The optimal speed trajectory should be a trade-off between the energy consumption and running time. Thus the original train trajectory optimization can be formulated as a bi-objective optimization problem in (5.8) where the train mass is set to the mean value $\bar{M}$, which is the sum of the empty vehicle mass and mean mass of the passengers, i.e. $\bar{M} = M_v + \bar{M}_p$. In the formulated optimization model, both objectives of minimizing the energy consumption and running time are equally important.

$$\min \begin{cases} E = f_1(V, \bar{M}) \\ T = f_2(V, \bar{M}) \end{cases} \quad (5.8)$$

In real operation, the train is required to arrive at the destination at time T and should be subject to speed and acceleration limits of each subsection and the driving rules stated in Section 5.2.2. The corresponding constraints are shown in (5.9).

$$s.t. \left\{ \begin{array}{l} v_{1,s} = v_{n,e} = 0 \\ v_{i,e} = v_{i+1,s} \ (i = 1, \dots, n-1) \\ s(0) = 0; s(T) = S \\ v_{i,s}, v_{i,c}, v_{i,b} \text{ and } v_{i,e} \leq v_{i,\max} \ (i = 1, \dots, n) \\ v_{i,s} \leq v_{i,c}; v_{i,e} \leq v_{i,b} \ (i = 1, \dots, n) \\ |a_i| \leq a_{i,\max} \ (i = 1, \dots, n) \end{array} \right. \quad (5.9)$$

5.2.3.2 Scheme Robustness (SR)

Previous research results have suggested that the main uncertain factor affecting the train operation is the passenger load dependent train mass. One driving scheme with a certain set of speed control variable V may be valid for the specific train mass values but not for others. The scheme robustness (SR) in this chapter proposed is used to guarantee the validity of the chosen scheme V even under the worst case. For a specific subsection with a particular set of driving control variables $V_i = (v_{i,s}, v_{i,c}, v_{i,b}, v_{i,e})$, the corresponding acceleration, coasting and braking distances can be confirmed based on the train model (5.1)-(5.5). While before producing a sectional train trajectory, an intermediate variable, the cruising time $t_{i,cr}$ needs to be calculated to determine the cruising distance $d_{i,c} = t_{i,cr} \cdot v_{i,c}$ accordingly. An iterative method is adopted to calculate the cruising time as shown in the flowchart in Figure 5.3. When a set of driving control variables of a subsection with a particular train mass value M is input, initially the cruising time $t_{i,cr}$ is assumed as 0, and the corresponding running distance d can be calculated. If $d = S_i$, where S_i is the distance of the subsection, it implies that the train can reach the end point of the subsection under (V_i, M) with $t_{i,cr} = 0$, hence $SR=1$. While $d < S_i$ implies that a valid cruising time value $t_{i,cr} > 0$ must exist. Then the binary search (or half-interval search) is used to find the cruising time value. Conversely, $d > S_i$ implies that a valid cruising time value can not be found under (V_i, M) . Consequently,

the scheme (V_i) is invalid under train mass M , hence $SR=0$. The bi-objective optimization problem in (5.8)-(5.9) is solved under the mean mass value $\bar{M}$. The worst case – the case most likely resulting in the scheme invalidity must occur at either the minimum $M_{\min}$ (empty vehicle mass) or the maximum $M_{\max}$ (full-load train mass). Evaluation of SR, for each selected driving scheme (V_i) should be performed by applying either $M_{\min}$ or $M_{\max}$ instead of average $\bar{M}$. If the results satisfy Equation (5.10), which is a logical constraint added in the original optimization model (5.8), the chosen driving scheme passes the scheme robust requirement. Taking an example as shown in Figure 5.4 with initial speed and end speed equal to 0, i.e. $v_{i,s} = v_{i,e} = 0$, the chosen scheme is valid with train mass of 500 tons. However, when the train mass increases to 580 tons, even if the cruising time is 0, the running distance is far longer than the sectional distance 20 km. In this case, the scheme (0, 55 m/s, 45 m/s, 0) is regarded as a non-scheme-robust scheme. i.e. $SR(0, 55, 45, 0, 580) = 0$. It should be noted that the driving scheme of each subsection needs to be checked to guarantee the validity under the extreme train mass values, i.e. $SR(V_i, M_{\min} | M_{\max}) = 1$ ($i = 1, \dots, n$), so that the whole train speed trajectory V is valid.

$$SR(V_i, M_{\min}) = 1 \text{ and } SR(V_i, M_{\max}) = 1 \quad (5.10)$$

$$SR(\cdot) = \begin{cases} 0 & \text{invalid scheme} \\ 1 & \text{valid scheme} \end{cases} \quad (5.11)$$

5.2.3.3 Performance Robustness (PR)

Scheme robustness, which implies the feasibility of the chosen scheme even under the worst train mass case, can be distinguished by the performance robustness. The energy consumption and running time of the chosen driving scheme should be affected as little as possible due to the train mass variation. This is referred to as performance robustness (PR) of the driving scheme and it is evaluated by the scheme sensitivity, which can be formulated as (5.12). Obviously, a driving scheme with low sensitivity to the variation of the passenger load is preferred and also means the energy consumption and running

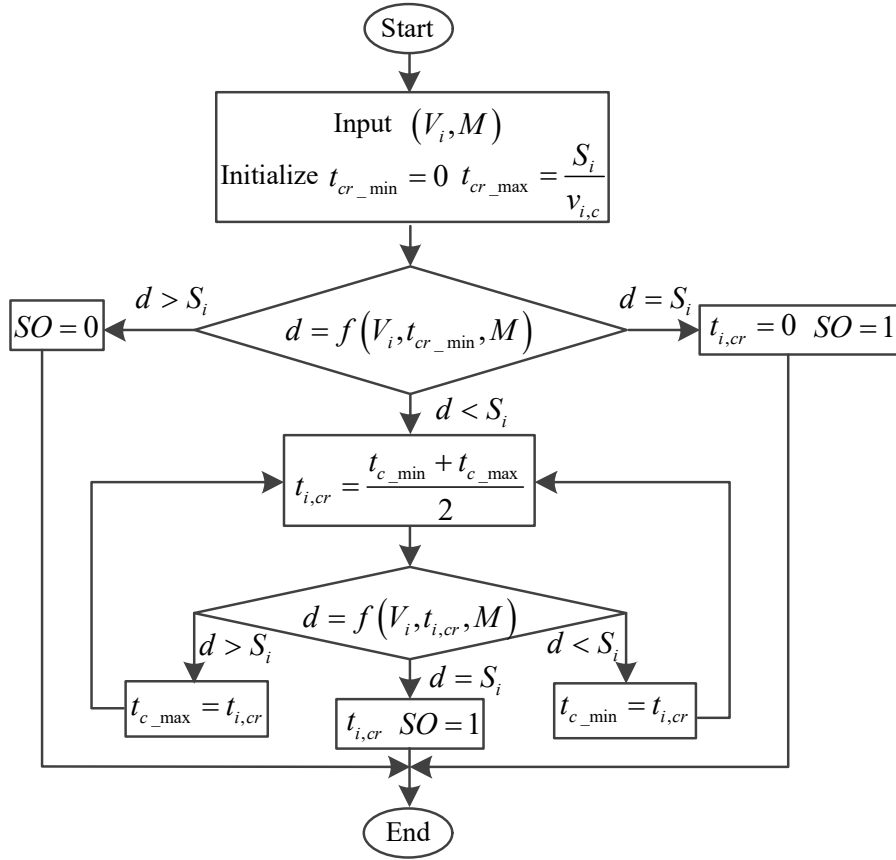
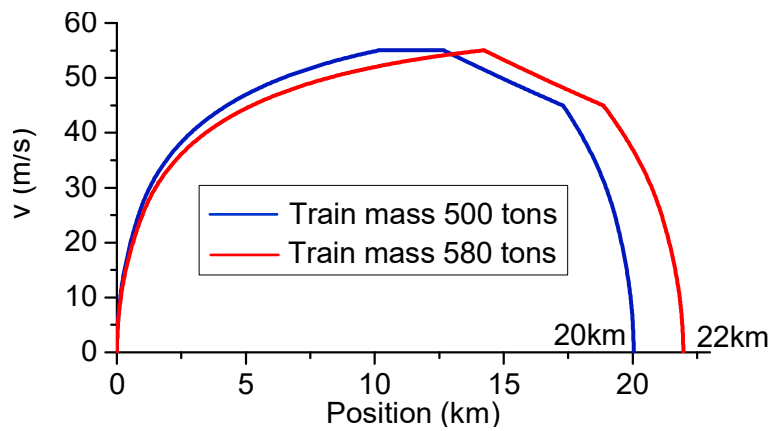
Figure 5.3: Flowchart of SO evaluation and $t_{i,cr}$ calculation.

Figure 5.4: Scheme invalidity caused by passengers' randomness.

time in the whole journey will not deviate far from their expected values.

$$PR = \max \left(\lambda_1 \cdot \frac{|t - t_{\min}|}{t} + \lambda_2 \cdot \frac{|E - E_{\min}|}{E}, \lambda_1 \cdot \frac{|t - t_{\max}|}{t} + \lambda_2 \cdot \frac{|E - E_{\max}|}{E} \right) \quad (5.12)$$

where λ_1 and λ_2 are the weighting factors. $\lambda_1, \lambda_2 \in [0, 1]$ and $\lambda_1 + \lambda_2 = 1$. And

$$\begin{cases} t_{\min} = T(V, M_{\min}); E_{\min} = E(V, M_{\min}) \\ t_{\max} = T(V, M_{\max}); E_{\max} = E(V, M_{\max}) \\ t = T(V, \bar{M}); E = E(V, \bar{M}) \end{cases} \quad (5.13)$$

Compared with the energy consumption and the running time, the performance robustness is often considered to be less important and hence it can be regarded as a subordinate objective. The main goal is still to find the scheme-robust Pareto solutions from the two-dimensional (2-D) plane of energy consumption and running time. Then the Pareto solutions are further filtered considering the performance robustness, meanwhile maintaining the Pareto spread and evenness.

In summary, the robust optimization problem for the train speed trajectories can be described as: Firstly without considering the uncertainty of the train mass, the original optimization problem is formulated as (5.8) with constraints (5.9). Then the scheme robustness (SR) is taken as the constraint (5.10) to filter out the driving schemes that cannot fit all train mass values. Finally, the performance robustness (PR) in (5.12) is considered in the proposed p-NSGA-II introduced in Section 5.3 to guide the search to select the driving schemes that are affected as little as possible by the train mass uncertainty. Notably, for a specific driving strategy, both the SR and PR are two different robustness indicators which are used to evaluate the performance of solutions at different stages of the optimization.

5.3 Optimization Algorithm – *p*-NSGA-II

In the robust optimization model of the speed trajectories, the performance robustness has a lower priority than energy consumption and running time. In this case, the performance robustness criterion can be seen as a type of DM preference. Thus the whole

problem becomes a DM preference-based bi-objective optimization. The DM preference is specified as aspirations, leading the search to gradually converge towards the DM region of interest (ROI). While existing preference-based approaches mostly rely on a reference point or a reference direction [243, 244, 250], these are not adopted in the optimization problem proposed here. In this section, a new DM preference-based optimization approach is proposed, which is extended by original NSGA-II and named as p-NSGA-II. The proposed p-NSGA-II is a type of interactive DM approaches. In an interactive decision-making approach, the DM preferences are incorporated progressively during the optimization process. The p-dominance criterion incorporating the DM preference is involved in each iteration. This can reduce the searching space and enable a DM effectively guiding the search towards regions of interest and away from exploring non-interesting solutions. The DM preference in the proposed optimization procedure is based on performance robustness and is manifested through a modification of the dominance relation.

5.3.1 Definition of *p*-Dominance

Most MOEAs are based on the nondomination relation. In this section, the nondomination relation is briefly introduced and a new dominance relation - preference-dominance (p-dominance) for dealing with DM preference is developed from this. This combines the original nondomination principle and DM preference. The main characteristic of p-dominance is that solutions located at the Pareto front can be further selected based on the DM preference. Given a general form of the multi-objective optimization problem:

$$\min (f_1(x), f_2(x), \dots, f_K(x)) \quad \text{s.t. } x \in X \quad (5.14)$$

where x is the vector of the decision variables, X represents the set of feasible solutions, and $f_k(x)$ ($k = 1, 2, \dots, K$) are the various objective functions. It is assumed that every feasible solution x_p has three attributes:

1. *Nondomination rank* (x_p^{n-rank})
2. *Preference rank* (x_p^{p-rank})

3. Crowding distance (x_p^{cd})

The nondomination relation can be described as: for two feasible solutions x_p and x_q , if

$$f_k(x_p) \leq f_k(x_q) \quad \forall k = 1, 2, \dots, K \quad (5.15)$$

with existing at least one integer in k satisfying $f_k(x_p) < f_k(x_q)$, then x_p dominates x_q (x_p has a lower nondomination rank than x_q). In other words, if a solution is not dominated by any other solutions, it is located at the first nondomination rank. The set of solutions in the first nondomination rank constitutes the Pareto front. Based on the above principle, the nondomination ranks x^{n-rank} of all solutions can be sorted.

The attribute of crowding distance, which has been introduced in [114], reflects the density of solutions surrounding the particular proposed solution x_p . To obtain an estimate of the density of solutions around a particular solution in the population, the average distance of two points on either side of this point along each of the objectives is calculated by (5.16).

$$x_p^{cd_k} = \frac{f_k(x_{p+1}) - f_k(x_{p-1})}{f_k^{\max} - f_k^{\min}}, \quad x_p^{cd} = \sum_{k=1}^K x_p^{cd_k} \quad (5.16)$$

where x_{p+1} and x_{p-1} are adjacent solutions to x_p . $f_k^{\max}$ and $f_k^{\min}$ represent the maximum and minimum values of k -th objective respectively. The solutions with a larger crowding distance are preferred, and it also implies that these solutions are in a less crowded region. The approach for evaluating the preference ranks will be illustrated in Section 5.3.2.

Based on the above three attributes, the Preference–Dominance Relation is defined as:

Definition (Preference – Dominance Relation): Given two solutions x_p and x_q , if one of the following statements is satisfied, x_q is p -dominated by x_p .

$$\text{if } (x_p^{n-rank} < x_q^{n-rank})$$

$$\text{or } (x_p^{n-rank} = x_q^{n-rank} \text{ and } x_p^{p-rank} < x_q^{p-rank})$$

$$\text{or } (x_p^{n-rank} = x_q^{n-rank} \text{ and } x_p^{p-rank} = x_q^{p-rank} \text{ and } x_p^{cd} > x_q^{cd})$$

That means, for two solutions with different nondomination ranks, the one with the lower rank is preferred. Then if two solutions are located with the same nondomination rank, the one with a lower preference rank is preferred. Finally the crowding distance attribute plays a minimum role in the p-dominance. If and only if both solutions are located in the same nondomination and preference ranks, the crowding distance will determine the ultimate p-dominance relationship between both solutions.

5.3.2 Preference Ranking

Different from the optimization objectives, the DM preference usually functions as a filter to guide the solutions towards the region of interest (ROI). Generally speaking, the expected ROI is a part of the optimal Pareto front of the original optimization problem. In some cases, the DM preference is defined by the distance between the solutions and reference points. At times, the preference is described as a convergence reference direction. They evolve accordingly to reference-point and reference-direction based DM algorithms. However, more generally, the DM preference is evaluated by defining the preference function based on a specific optimization problem. For example, the preference function for the problem of train speed trajectory optimization is the performance robustness expressed by (5.12).

It is assumed, in this section, that the preference function is predefined and the corresponding values for all solutions are evaluated in advance, so the approach to sort out their corresponding preference ranks is described below.

Taking $p(x)$ as the preference function for a bi-objective optimization problem defined by (5.14) with $k=1,2$, the DM preference is specified to minimize this function. For evaluating the preference rank of each solution, one can assume that there is a set of nondominated solutions $x_1, x_2, x_3, \dots, x_P$ located in the same front, their corresponding objective function values constitute the set of points in the two-dimensional (2-D) solution plane, as shown in Figure 5.5 (a). Furthermore, with their preference function values evaluated by $p(x)$, the original set of 2-D points is extended to the points cloud in three-

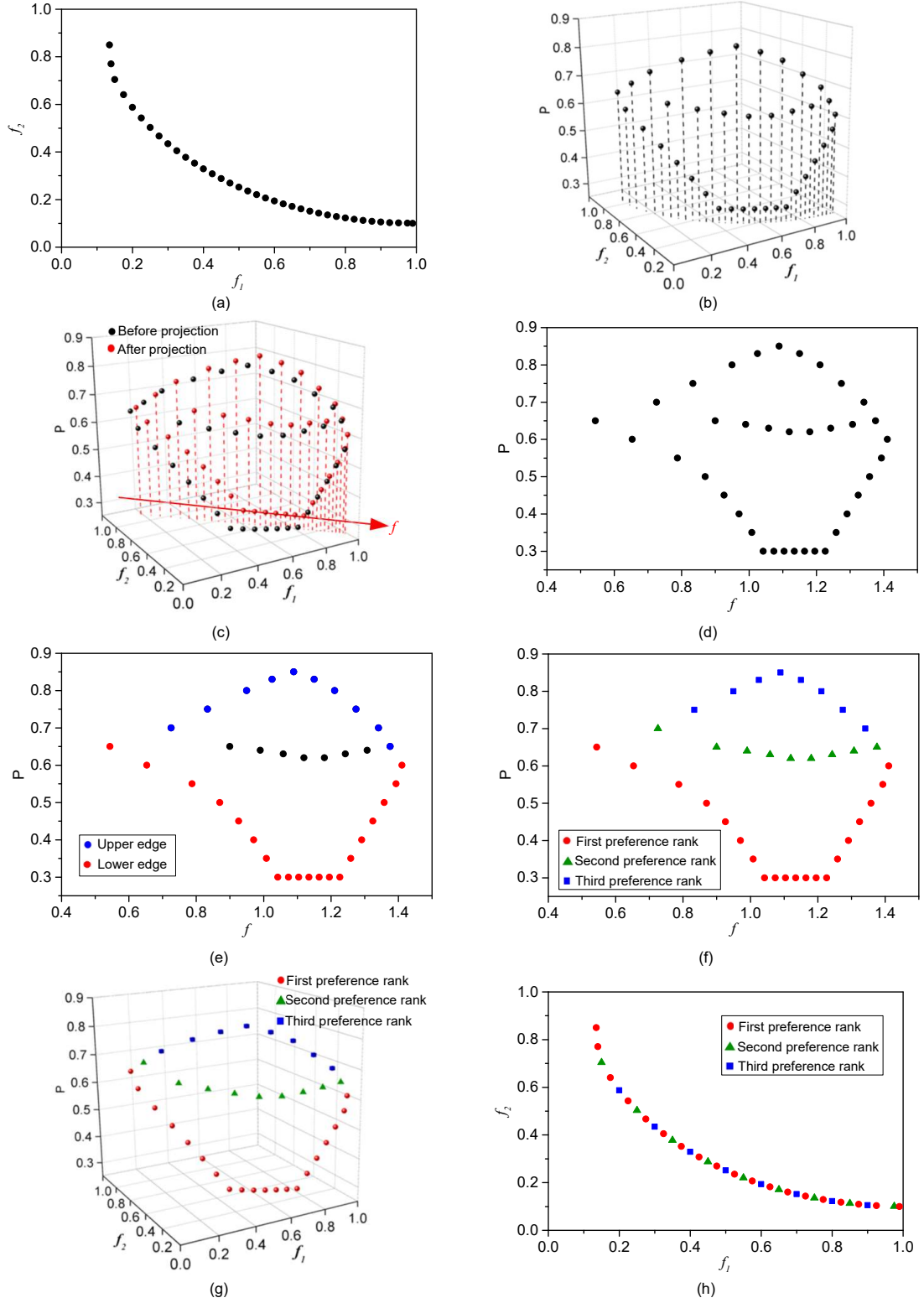


Figure 5.5: Procedures of preference ranking.

dimensional (3-D) space as illustrated in Figure 5.5 (b). Note that in this graph x-axis and y-axis represent both objectives $f_1(x)$ and $f_2(x)$, and z-axis represents the preference function $p(x)$.

The proposed method for deriving the preference rank for each solution can be divided into three steps – projection of solutions, outline points identification and preference ranking.

5.3.2.1 Projection

The aim of this preliminary step is to project all the solution points in the 3-D space plot in Figure 5.5 (b) onto a new 2-D plane, hence facilitating rank sorting. Since the corresponding coordinate of a solution x_p in Figure 5.5 (b) is $(f_1(x_p), f_2(x_p), p(x_p))$, one can define a new axis, $f(x)$ -axis, which collapses axes $f_1(x)$ and $f_2(x)$, and then project each solution point onto the new 2-D plane defined by $(f(x), p(x))$. The value of each solution x_p in $f(x)$ -axis can be calculated by:

$$f(x_p) = \sqrt{(f_1(x_p))^2 + (f_2^{\max}(x) + f_2^{\min}(x) - f_2(x_p))^2} \quad (5.17)$$

where $f_2^{\max}(x)$ and $f_2^{\min}(x)$ represent, respectively, the maximum and minimum values of $f_2(x)$, as x ranges over the set of all nondominated solutions. In this way, all solutions are mapped to the $f(x)$ -axis, which is shown in Figure 5.5 (c). Also according to the characteristics of nondominated solutions, all solutions do not overlap on the $f(x)$ -axis and the density of the solutions can be maintained to the utmost extent. As each solution's $p(x)$ value is retained, all solutions now have their respective $f(x)$ -axis and $p(x)$ -axis values and hence can be projected to the 2-D plane with $f(x)$ and $p(x)$ axes, as shown in Figure 5.5 (d).

5.3.2.2 Outline Points Identification

This step aims to identify the outline points of all solutions in the new 2-D plane defined by $f(x)$ and $p(x)$ axes. α -shape method is adopted which is widely applied for finding the outline points of a point set [251]. Algorithm 1 (α shape method) illustrates how to determine whether the solution points are the outline points of the shape.

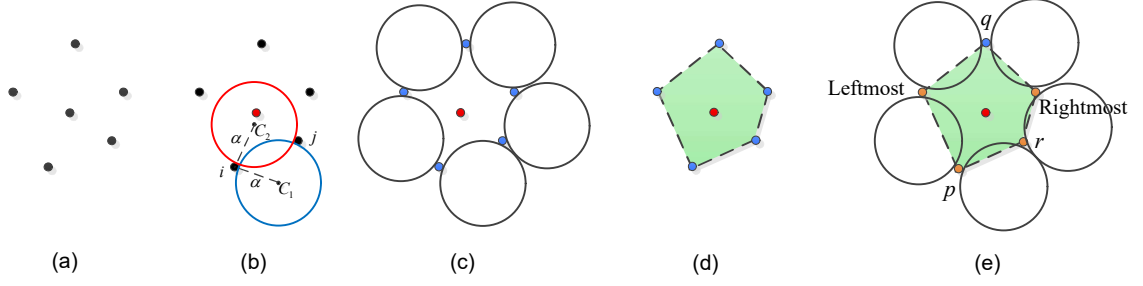


Figure 5.6: Outline points identification.

Algorithm 1 α shape method

- 1: Input N solution points with their coordinates
 - 2: Set the circle radius α
 - 3: Select a pair of points i and j from the solution points
 - 4: Calculate the length L_{ij} between points i and j
 - 5: IF $L_{ij} \leq 2\alpha$
 - 6: Construct two circles with same radius α that pass through points i and j , see Figure 5.6 (b)
 - 7: Calculate the circle center coordinates C_1 and C_2
 - 8: Calculate the lengths L_{c_1n} and L_{c_2n} ($n = 1, \dots, N - 2$) between the circle center (C_1 or C_2) and other points except for points i and j
 - 9: IF $L_{c_1n} > \alpha$ or $L_{c_2n} > \alpha$ ($n = 1, \dots, N - 2$)
 - 10: Points i and j are identified as outline points
 - 11: ENDIF
 - 12: ENDIF
 - 13: Return to Line 3 until all point pairs of size $\frac{N \cdot (N-1)}{2}$ are checked
 - 14: Output all outline points
 - 15: END
-

It is noted that, in Algorithm 1 (α shape method), if the lengths L_{c_1n} or L_{c_2n} ($n = 1, \dots, N - 2$) are larger than α , that means there are no points contained inside the circle with radius α , whose circle center is C_1 or C_2 . At this moment, the selected pair of points i and j are located at the edge of the shape constructed by the discrete points, i.e. outline points.

A simple example is used to explain this method. As shown in Figure 5.6 (a), there are six points in a 2-D plane. A pair of points i and j are selected and labeled in Figure 5.6 (b). Two circles (blue circle and red circle) with radius α can be constructed which pass through both points i and j as can be seen in Figure 5.6 (b). Although the red circle

contains one other point (red point), there is no other point locating within the blue circle. Thus both points i and j are therefore identified as outline points. In the same way, all outline points (blue points in Figure 5.6 (c)) can be identified, and the shape constituted by the points is shown in Figure 5.6 (d), while the red point is not the outline point. For this method, the circle radius α will affect the result of the outline points identification. If α is too small, the set of points will be split into multiple shapes. If α is too large, the shape will be rather irregular. In this chapter, radius α is set to the minimum value to ensure that all points are grouped in one region. Then the classification of lower and upper outline points is achieved as follows: when the outline points are identified, it is easy to find the leftmost point based on the value of the f -axis as shown in Figure 5.6 (e). The leftmost point is determined as the first lower edge outline point. During the process of outline point identification, the leftmost point with two identified outline points p and q can constitute two point pairs (L, p) and (L, q) satisfying the conditions of outline point identification. These two points p and q are considered as lower and upper edge outline points respectively. Similarly, considering one of the two identified outline points like point p , besides the point pair (L, p) , there exists another point r that can constitute another point pair (p, r) with point p . This point r can be considered located in the same outline with point p , lower outline or upper outline. The process is repeated until the rightmost point is searched. In this way, the whole set of the outline points is divided into two sets by the leftmost point and rightmost point. Then, the average p -axis values of both sets of points are calculated. The point set with smaller p -axis values can be seen as the lower outline point set labeled in orange in Figure 5.6 (e).

Applying the above described scheme to all the solution points in Figure 5.5 (d), the outline points can be identified, and these can then be divided into lower edge outline points (red points) and upper edge outline points (blue points) as illustrated in Figure 5.5 (e). While the black points are not the outline points.

5.3.2.3 Ranking

Since the DM preference aims at minimizing $p(x)$, those solution points in Figure 5.5 (e), possessing lower preference values and constituting the lower edge of the shape, are preferred. These solutions are assigned the first preference rank. For the rest of the solutions, the outline points identification and ranking procedure are repeated until all solutions are sorted into different preference ranks. In Figure 5.5 (f), the solutions are sorted into three ranks and are remapped into the original 3-D space as shown in Figure 5.5 (g). Finally, all the original solutions located in the same nondomination front as those illustrated in Figure 5.5 (a) are sorted into different preference ranks as presented in Figure 5.5 (h).

5.3.3 Procedure of p -NSGA-II

Incorporating the proposed p -dominance relation and preference ranking method into the typical multi-objective evolutionary algorithms (MOEAs), a variant of the original NSGA-II is proposed which is called p -NSGA-II. Its implementation procedure is now described:

- Step 1 GA operation: Initially, a random parent population P_0 of size N is created. To ensure generality, the parent population is denoted as P_i in the subsequent iterations. After applying GA operators on parent population P_i , including selection, crossover and mutation, the offspring population Q_i also of size N is created. Then the parent and offspring populations P_i and Q_i are combined to form a new population C_i of size $2N$.
- Step 2 Fitness and preference value evaluation: For each individual in the population C_i , their corresponding objective functions $f_1, f_2, \dots, f_k$, are evaluated together with the preference function $p(x)$.
- Step 3 Nondomination rank sorting: Based on the nondomination relation and objective functions evaluated, the nondomination rank of the individuals in a

population C_i can be sorted. The sorting is according to the objective function values of the ones not being dominated by any other individuals hence are the most nondominated and are assigned Rank 1, and the individuals only dominated by individuals in Rank 1 are assigned Rank 2, and so on up to the t -th rank in the set. Once the sum of solutions from the first rank to t -th rank exceeds N , only solutions from first to $(t - 1)$ -th ranks are chosen, while the solutions in t -th rank should be further sorted. The t -th rank is called the last nondomination rank.

- Step 4 Preference ranking: For the solutions in the t -th nondomination rank, they continue to be sorted into different preference ranks using the proposed performance ranking method in Section 5.3.2. Similarly, the solutions from the first to the $(h - 1)$ -th preference ranks are chosen in turn. While the solutions in the last preference rank, i.e. the h -th preference rank, will be operated in the next step.
- Step 5 Crowding distance sorting: The solutions in the t -th nondomination rank and h -th preference rank are sorted using the crowding-comparison operator. The solutions with larger crowding distance are chosen until the chosen solutions from Steps 3-5 fill all slots in a population, forming a new parent population P_{i+1} .
- Step 6 Stopping criterion: this is defined by the maximum number of iterations.

Steps 3-5 perform the p-dominance procedure. In the whole process, the elitism is ensured. All solutions will be automatically guided towards the Pareto front based on the nondomination relation. Then the solutions located at the Pareto front will continue to converge to the ROI according to the DM preference.

To assess the complexity of the algorithm, we consider one iteration with a population of size N and the basic operations and their worst-case complexities are as follows:

- 1) nondominated sorting is $O(KN^2)$
- 2) preference ranking is $O(N^3)$
- 3) crowding-distance assignment is $O(KN \log(N))$

4) p-dominance sorting is $O(N \log(N))$

where K represents the number of objectives. The computational complexities of the nondominated sorting and crowding-distance assignment operations have been discussed in [114]. Please refer to [114] for details. For preference ranking operation, it includes three steps: projection, outline points identification and ranking. The computational complexities of projection and ranking operations are $O(1)$. The outline points identification is achieved by the α -shape method. During this process, as illustrated in Algorithm 1, any two points will constitute a point pair. N points can constitute $N(N-1)$ pairs. For any other points except for the selected pair of points, it is necessary to check if they are enclosed by the circles constituted by the selected pair of points. It is obvious that the computational complexity of outline points identification is $O(N^3)$. Thus, the overall computational complexity of preference ranking operation is $O(N^3)$ which is governed by the outline points identification (α -shape method). While the computational complexity of p-dominance sorting is $O(N \log(N))$. By summarizing the above analysis for the different operations in the proposed p-NSGA-II, the overall complexity can be considered as $O(N^3)$, which is governed by the preference ranking of the p-NSGA-II. Furthermore, it should be noted that, since the parent population and offspring population are mixed together during the algorithm, the actual size of the population is $2N$. Thus the actual computational complexities need to be adjusted correspondingly by replacing N with $2N$.

Combining the optimization model for train speed trajectories as illustrated in Section 5.2, the whole framework for searching the robust driving schemes by the proposed p-NSGA-II is summarized in Figure 5.7, and details are given as follows. Step 1: Initialization. Randomly initialize the $2N$ driving strategies (V^1) to (V^{2N}) at the beginning of the algorithm and each driving strategy (V^i) corresponds to one specific train speed trajectory. Step 2: Apply the $2N$ driving strategies one by one to the train model (5.1)-(5.5) to calculate their energy consumption and running time (E_i, t_i) under the mean value of the train mass using (5.6) and (5.7). Besides, under the worst scenario, evaluate the performance sensitivity P_i of each driving strategy based on the maximum energy and running time deviations by (5.12). Step 3: Verify the scheme robustness (SR) of each

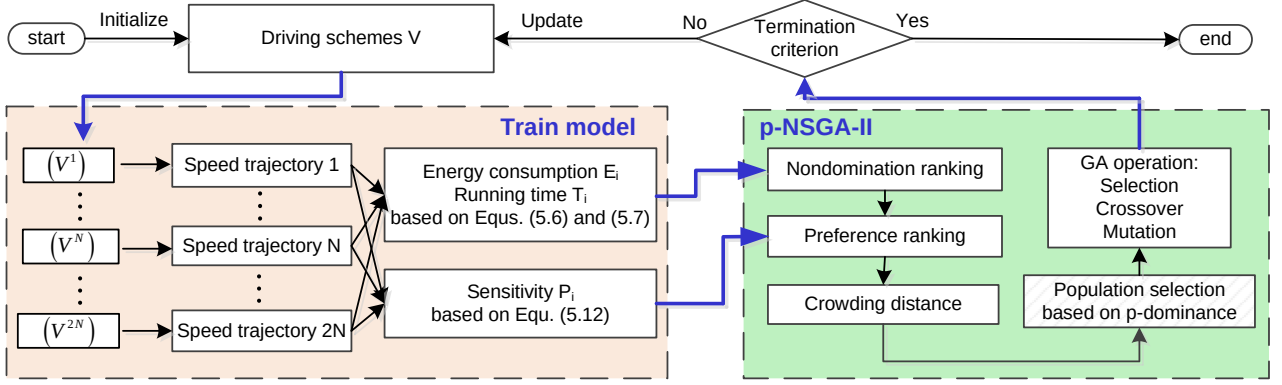


Figure 5.7: Framework for searching the robust driving schemes.

driving strategy and remove non-robust solutions. Step 4: For the remaining driving strategies, determine the nondomination rank and calculate the crowding distance with the energy consumption and running time (E_i, t_i) based on Section 5.3.1. Taking performance sensitivity P_i as the DM preference in the proposed p-NSGA-II, conduct the preference ranking considering the energy consumption, running time and also sensitivity (E_i, t_i, P_i) based on Section 5.3.2. Step 5: Given the nondomination rank, preference rank and crowding distance of each driving strategy, select N preferred driving strategies from the initial $2N$ driving strategies based on the principle of p-dominance defined in Section 5.3.1. Step 6: Produce N new offspring driving strategies using the genetic algorithm (GA) operations such as crossover and mutation. Step 7: Mix the parent set and newly generated offspring set by Step 6 to generate the new $2N$ driving strategies. Step 8: Return to Step 1 to repeat the procedures until the termination condition is satisfied. Notably, the railway decision maker (dispatcher) can set the preference according to (5.12) and the proposed p-NSGA-II is able to find the DM preference-based driving strategies accordingly.

5.4 Case Study and Discussions

To verify the effectiveness of the proposed optimization method, two case studies are performed using MATLAB R2021a on a PC with 2.80GHz Intel i7-7700HQ CPU and

16GB RAM. Both use British Rail Class 390 as the example, which has the characteristic curve as shown in Figure 5.1. The related parameters are listed in Table 5.1 [249]. Case 1, as a baseline case, only considers the basic resistance to verify the proposed p-NSGA-II. Case 2 considers basic resistance, additional resistance caused by the track gradients as well as various speed limits. The case studies confirm the effectiveness of the proposed p-NSGA-II in searching for the robust and optimal train speed trajectory that are suitable for real-life operations.

Table 5.1: Case Study Parameters

Parameter	Value
Journey distance S	20 km
Empty vehicle mass M_v	420,000 kg
Maximum passenger mass $M_{p-\max}$	160,000 kg
Basic resistance r_1	$1.456 + 0.0183v + 0.0034v^2$
Speed limit $v_{\max}$	55 m/s
Maximum traction/braking effort $F_{\max}$	200 kN
Maximum power $P_{\max}$	5000 kW
Regeneration efficiency η	0.8
Range of cruising speed v_c	[30, 55] m/s ([105, 200] km/h)
Range of braking speed v_b	[0, 55] m/s ([0, 198] km/h)

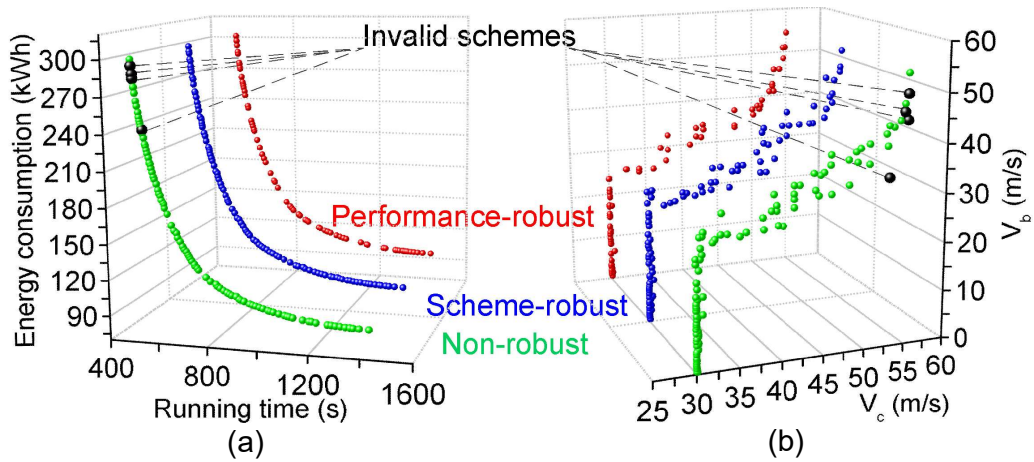


Figure 5.8: Comparisons of the Pareto fronts and solutions distribution under different situations in case 1. (a) Pareto fronts; (b) Solutions distribution.

5.4.1 Case 1

In this case, the whole track is on a flat plain and only the constant speed limit is considered. Thus the control variable is $V = (0, v_c, v_b, 0)$ where v_c and v_b need to be determined to get the set of driving schemes. The NSGA-II is applied first to solve the bi-objective train speed trajectory optimization problem defined by (5.8)-(5.9) without considering any robustness. For the NSGA-II, the solution number in a population is 100 and the maximum iteration number is set to 100. The crossover probability is 0.9 and mutation probability is 0.05. The train mass of 500 tons equaling the sum of empty vehicle mass (420 tons) and average passenger load (80 tons), is applied to the optimization model. The Pareto front obtained in this initial run is shown in Figure 5.8 (a) in terms of their two objective function values.

All Pareto solutions (green set) in Figure 5.8 (a) are checked by scheme robustness constraint in (5.10). Among the whole set, four solutions, labeled in black in Figure 5.8 (a), are non-scheme-robust, hence can not fit all operation conditions. The optimization procedure is implemented again with the scheme robustness applied as a constraint during NSGA-II iterations, hence all Pareto solutions are checked in each iteration and the non-scheme-robust solutions are filtered out. Consequently, the Pareto solutions (blue set) are all scheme-robust and the optimization result is also shown in Figure 5.8 (a). Figure 5.8 (b) shows the distributions of the non-scheme-robust solutions and scheme-robust solutions in terms of their v_c and v_b respectively. It can be seen that applying or not applying scheme robustness constraint does not significantly affect the distributions of the Pareto solutions. In general, the non-scheme-robust driving strategies are caused by insufficient braking distance and braking force. When the chosen driving strategy possesses a high cruising speed and a relatively low braking speed, the acceleration distance is prolonged to catch up with the target cruising speed as the train mass increases. Meanwhile, to decelerate the train to the set braking speed by the inertia from a high cruising speed, the coasting distance may be too long and the braking distance is likely insufficient. Thus this is also evident that as shown in Figure 5.8, the driving strategies with a big gap between the cruising and coasting speeds are not included in

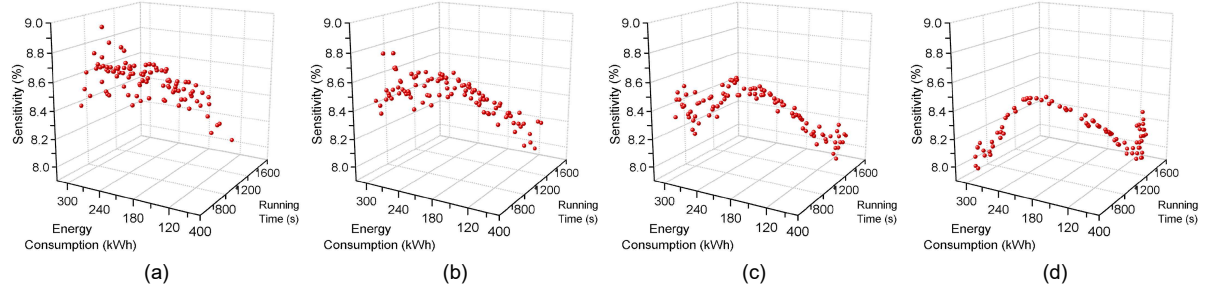


Figure 5.9: Iterations of p-NSGA-II in case 1. (a) 20 iterations; (b) 50 iterations; (c) 75 iterations; (d) 100 iterations.

the robust Pareto sets.

Considering the performance robustness of each solution, the proposed p-NSGA-II is adopted to produce a performance-robust Pareto front. Equation (5.12), as the DM preference function, is applied in the p-NSGA-II framework to evaluate the sensitivity of each driving scheme. The goal of the p-NSGA-II is to find solutions with lower sensitivity (more performance-robust). To achieve equilibrium on the robustness of energy consumption and running time, in this case, λ_1 and λ_2 in (5.12) are both set to 0.5. The parameters of GA operations are the same as above.

As the iteration goes on, the population gradually converges to the lower nondomination ranks, which is consistent with the description in Section 5.3. After 20 iterations, all solutions converge to the first nondomination rank. In the 3-D space, the x-axis, y-axis and z-axis represent energy consumption, running time and driving scheme sensitivity respectively, the solution distribution is shown in Figure 5.9 (a). As the iteration continues, from Figure 5.9 (b)-(d), it is apparent that the population is further guided towards the more performance-robust region.

The performance-robust Pareto front (red set) solved by p-NSGA-II and the solution distribution are also shown in Figs. 5.8(a) and (b) respectively. Compared with the scheme-robust Pareto front, the spread of the performance-robust Pareto front is less even than the former but is still acceptable. And the solution distribution is also not significantly changed. Table 5.2 lists the results for three different robust situations. It is shown that, when considering robustness, the spread of the Pareto fronts will not

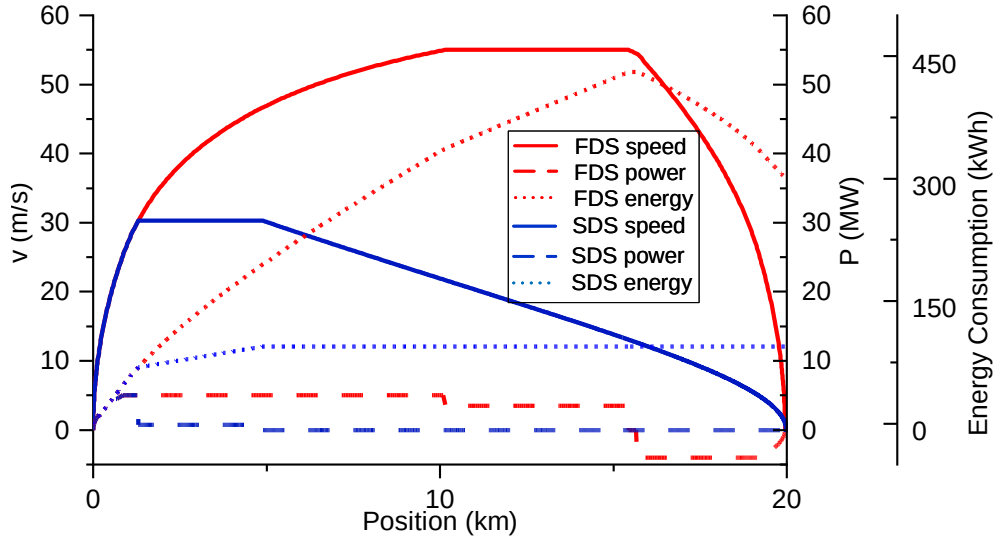


Figure 5.10: Fastest driving scheme and slowest driving scheme.

become worse compared to the Pareto front without considering robustness.

Figure 5.10 illustrates the fastest driving scheme (FDS) and the slowest driving scheme (SDS) among the performance-robust Pareto solutions. The FDS accelerates the train as much as possible to the maximum speed without any coasting operation. While for the slowest driving scheme (most energy-saving driving scheme), the cruising speed nearly equals the minimum speed limit. The coasting operation is maximally utilized to reduce energy consumption. The running time of FDS is only 36.5% of SDS, but consumes 3.19 times as much energy as the SDS.

In Figure 5.11 (a), the comparison of the performance-robust solutions (red balls) with the scheme-robust solutions (blue balls) under $\lambda_1 = 0.5$ and $\lambda_2 = 0.5$, demonstrates that the p-NSGA-II does produce a set of solutions with overall lower sensitivity to passenger load variation. To further explain the differences of robustness between both sets of solutions, each set of solutions is divided into three groups based on the running time. They are high-speed (HS) group (33 solutions), medium-speed (MS) group (33 solutions) and low-speed (LS) group (34 solutions), respectively. Figure 5.11 (b) presents, amongst the six groups, all three groups from the performance-robust solutions have better indices of robustness than the other three groups from scheme-robust solutions. To compare the overall robustness between the scheme-robust solutions and performance-

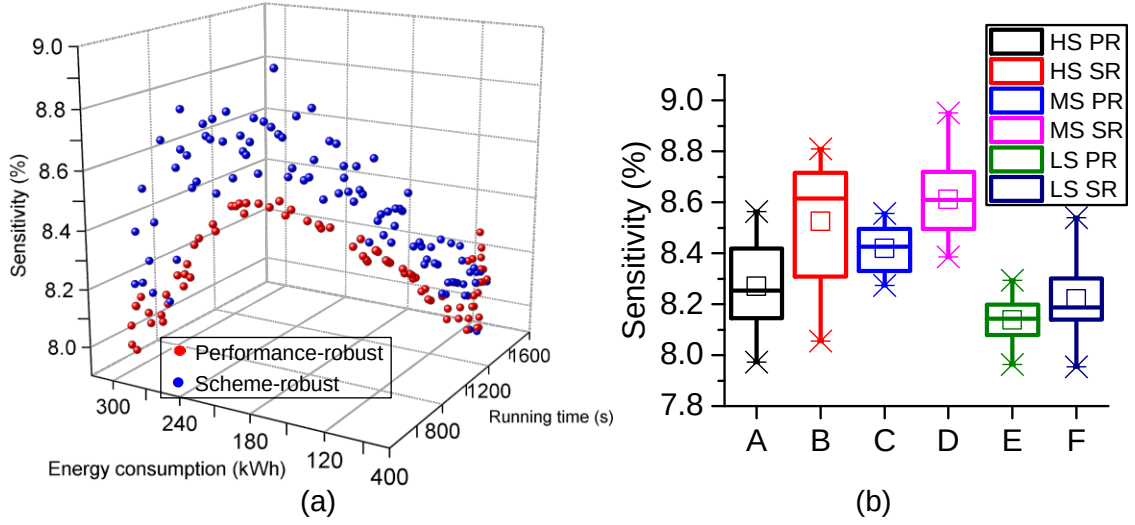


Figure 5.11: Comparisons of sensitivity between scheme-robust solutions and performance-robust solutions ($\lambda_1 = 0.5$, $\lambda_2 = 0.5$) in case 1.

robust solutions, the normalized average sensitivity values of both sets of solutions are calculated by (5.18), where S_{SR} and S_{PR} represent the sets of sensitivity values of the scheme-robust solutions and performance-robust solutions respectively. Compared to the scheme-robust solutions, the average sensitivity reduction (robustness improvement) of the performance-robust solutions is 40.59% calculated by (5.18). The superiority of the proposed p-NSGA-II is thus validated.

$$S_{SR/PR}^{ave} = \frac{1}{N} \sum_{n=1}^N \frac{S_{SR/PR}^n - \min(S_{SR} \vee S_{PR})}{\max(S_{SR} \vee S_{PR}) - \min(S_{SR} \vee S_{PR})} \quad (5.18)$$

$$R = \frac{S_{SR}^{ave} - S_{PR}^{ave}}{S_{SR}^{ave}} \cdot 100\% \quad (5.19)$$

To further analyze the effects of weighting factors, λ_1 and λ_2 , in performance robustness equation (5.12) on optimization results, another two sets of values are adopted. The first set is $\lambda_1 = 1$ and $\lambda_2 = 0$, this means only the robustness of the running time is considered, while the energy consumption robustness is ignored. Another set is $\lambda_1 = 0$ and $\lambda_2 = 1$, so only energy consumption robustness is considered, neglecting the running time. When the weighting factors are set to be $\lambda_1 = 0$ and $\lambda_2 = 1$, the objective is to find a set of optimal solutions with the best robustness for energy consumption by p-NSGA-II. While if the weighting factors are set $\lambda_1 = 1$ and $\lambda_2 = 0$, p-NSGA-II will produce a set of

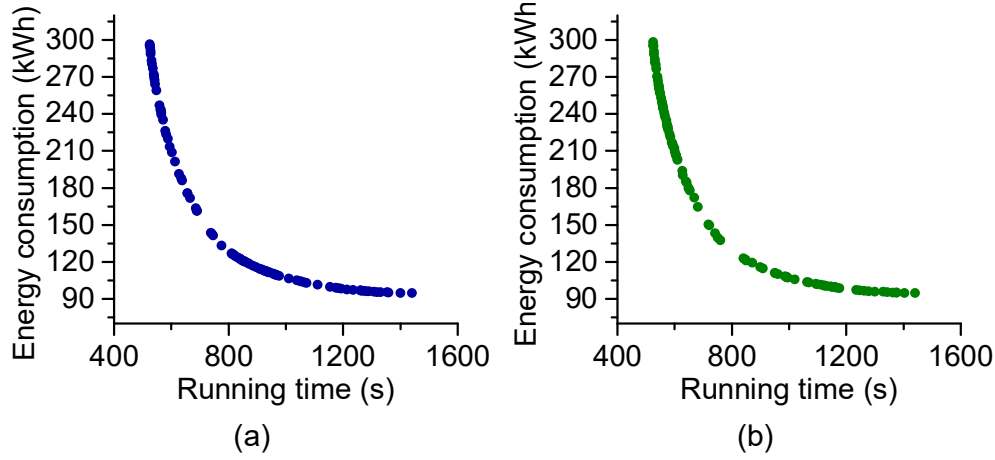


Figure 5.12: Pareto fronts of two sets of weighting factors. (a) $\lambda_1 = 1, \lambda_2 = 0$; (b) $\lambda_1 = 0, \lambda_2 = 1$.

optimal solutions with the best robustness for the journey time. When the weighting factors are set $\lambda_1 = 0.5$ and $\lambda_2 = 0.5$, a set of balanced-robust solutions are obtained. The Pareto fronts of both cases are shown in Figs. 5.12 (a) and (b). To compare each solution, the sensitivities of the running time and energy consumption are evaluated by (5.20) and (5.21) below respectively.

$$T_s = \max\left(\frac{|t - t_{\min}|}{t}, \frac{|t - t_{\max}|}{t}\right) \quad (5.20)$$

$$E_s = \max\left(\frac{|E - E_{\min}|}{E}, \frac{|E - E_{\max}|}{E}\right) \quad (5.21)$$

The comparison of the sensitivity of the running time and energy consumption under

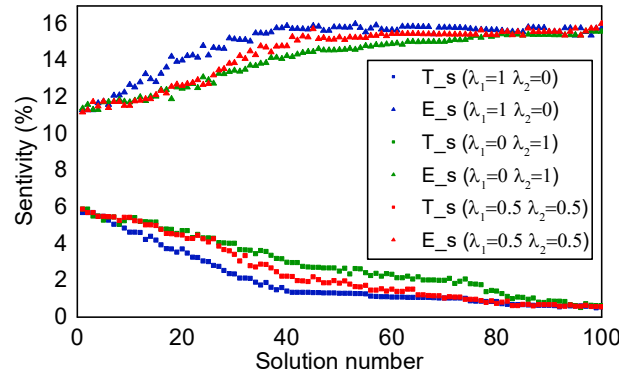


Figure 5.13: Comparison of solution sensitivity under three different sets of weighting factors in case 1.

three sets of weighting factors is shown in Figure 5.13 and Table 5.2. In Figure 5.13, 100 solutions under each set of weighting factors are sorted based on the running time. The number 1 corresponds to the solution with the shortest running time, while the number 100 corresponds to that with the longest running time. From Figure 5.13 and Table 5.2, it is evident that:

1. For all three sets of weighting factors, as the journey time increases, the running time sensitivity decreases but energy consumption sensitivity increases. The sensitivities of running time and energy consumption are negatively correlated. Under the driving schemes with a high average speed, the variation of energy consumption due to the train mass uncertainty is relatively small. While those driving schemes with a low average speed perform well in running time robustness.
2. The weighting factors determine the priority of DM preference. Choosing different sets of weighting factors is to trade off the robustness of running time and the energy consumption. If only the robustness of running time is considered, the solutions' robustness of energy consumption will perform poorly. On the other hand, when only consider the robustness of energy consumption, the robustness of running time will be poorer. When $\lambda_1 = 1$ and $\lambda_2 = 0$, the solutions are most robust for running time. When $\lambda_1 = 0$ and $\lambda_2 = 1$, the set of solutions are most robust for energy consumption. The solutions under any other weighting factors, for example $\lambda_1 = 0.5$ and $\lambda_2 = 0.5$, will be somewhere in between.
3. The average energy sensitivity is 13.7% for the most energy robust set ($\lambda_1 = 0$, $\lambda_2 = 1$) compared to 14.4% of the most time robust set ($\lambda_1 = 1$, $\lambda_2 = 0$). Take 15% energy deviation as the threshold since the maximum energy deviations are larger than 15% without optimization as shown in [229]. The energy sensitivity of 62 solutions out of 100 (62%) in the most energy-robust set is lower than the threshold, while only 28 solutions (28%) in the most time-robust set are lower than the threshold. The most time robust set has a lower average time sensitivity of 1.6% compared to 2.5% of the most energy-robust set. The average delay time of the most

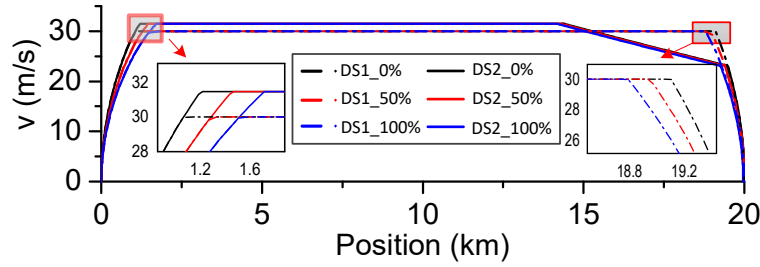


Figure 5.14: Comparison of time-robust and non-robust driving strategies.

time-robust set is 13.7 s compared to 18.2 s of the most energy robust set. Based on the experience from Beijing Yizhuang Line Links [229, 239], assume the time sensitivity threshold is set to 4%, the most time robust set has 85% satisfactory rate compared to 70% of the most energy-robust set. The effectiveness of the proposed p-NSGA-II is therefore evident.

A comparison of a time robust speed profile and another speed profile only catching up with the braking curve is performed. For the first driving strategy, a target cruising speed 30 m/s without optimization is set. The train is accelerated to the target speed and then kept the constant speed until the train reaches the latest braking point. The second driving strategy (31.5 m/s, 23.1 m/s) is optimized by the proposed p-NSGA-II under $\lambda_1 = 1$, $\lambda_2 = 0$ (most time robust). The speed trajectories under different passenger loads are shown in Figure 5.14. The journey time is 725 s under empty load, 738 s under 50% load and 753 s under 100% load for DS1, and 726 s, 738 s and 749 s for DS2. It is evident that, under the mean value of the train mass, the running time of both driving strategies is the same. While the running time deviations of both driving strategies under the mean value of the train mass are 13 s and 12 s to the empty load, and 15 s and 11 s to the full load. The maximum deviations of running time for both driving strategies are 15 s and 12 s respectively, corresponding to the maximum running time sensitivities of 2.0% and 1.6%. Thus the performance of the proposed p-NSGA-II is validated.

The performance robustness reflects the maximum sensitivities of energy consumption and running time to the variation of the passenger load. This performance value is primarily determined by both the resultant driving strategies that are generated by our

algorithm and by the DM's preference which are reflected in the two preference weights λ_1 and λ_2 . In other words, infinite solutions may exist in the Pareto front while their sensitivities to energy consumption and running are different. The final selected Pareto solutions are determined by the DM (dispatcher) preference and are generated by the proposed p-NSGA-II.

To further illustrate the benefits of our proposed algorithm p-NSGA-II and the optimization framework, the comparisons between robust optimization (RO), stochastic optimization (SO) and our proposed method are performed. A widely adopted framework of the uncertain multi-objective optimization is shown in the following [230, 252]:

$$\min(f_1(\hat{x}, \bar{m}), f_2(\hat{x}, \bar{m}), \dots, f_K(\hat{x}, \bar{m})) \quad (5.22)$$

$$s.t. \frac{\|\hat{f}^P(\hat{x}, m) - \hat{f}(\hat{x}, \bar{m})\|}{\|\hat{f}(\hat{x}, \bar{m})\|} \leq \eta \quad \hat{x} \in S \quad (5.23)$$

where $\hat{f}(\hat{x}) = (f_1(\hat{x}), f_2(\hat{x}), \dots, f_K(\hat{x}))$. $\hat{x}$ is the vector of the control variables. m represents the uncontrollable uncertain parameters. $\bar{m}$ is the mean value of the uncontrollable uncertain parameters. $\hat{f}^P$ represents the perturbed objective vector and η is the maximum value of sensitivity required so that the decision maker can adjust the maximum value of the sensitivity of the solutions. The perturbed objective vector can be chosen either to be the worst case to formulate a RO problem, or to be the mean effective value of the neighborhood to formulate a SO problem. In the following, both optimization models will be generated and the two objectives still remain to be the same, i.e. minimizing the energy consumption and running time for the given mean value of the train mass. The sensitivity η is set to different values. Notably, the perturbed objective vector in the SO problem needs to be calculated by the Monte Carlo method, and assume the mass of passengers is distributed as discrete normal distribution $M \sim N(\mu, \sigma^2)$ for a specific substation and operational period. The RO optimization model in (5.22) and (5.23) was adopted in [230]. Both RO and SO are performed by traditional NSGA-II.

Figs. 5.15-5.16 show the Pareto fronts and the sensitivities by RO. In Figure 5.15, the dark green and pink dots represent the energy sensitivity and time sensitivity of each solution respectively. In Figs. 5.15 (a)-(d), η varies from 0.02 to 0.06, and it is obvious that

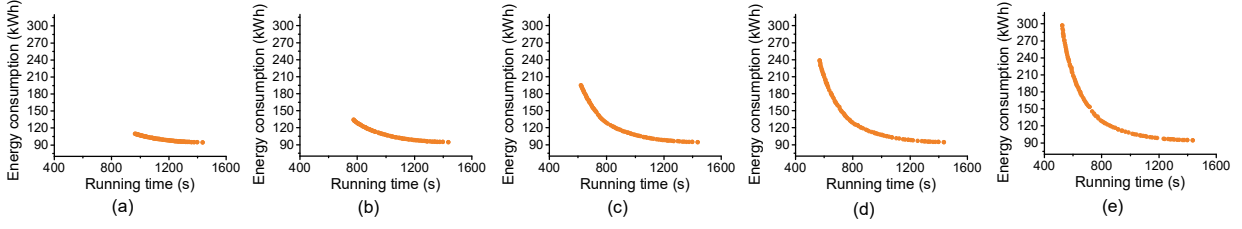


Figure 5.15: RO Pareto fronts. (a) $\eta = 0.02$; (b) $\eta = 0.03$; (c) $\eta = 0.05$; (d) $\eta = 0.06$; (e) $\eta = 0.07$.

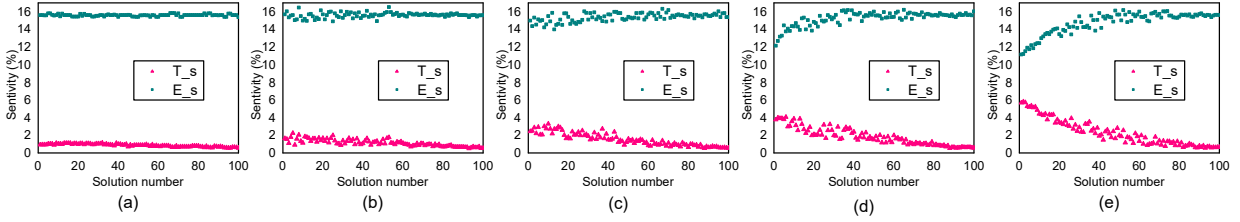


Figure 5.16: RO sensitivities. (a) $\eta = 0.02$; (b) $\eta = 0.03$; (c) $\eta = 0.05$; (d) $\eta = 0.06$; (e) $\eta = 0.07$.

the solution distributions are narrowed down compared to the solutions generated by our proposed p-NSGA-II. As shown in Table 5.2, the Pareto distributions of energy decrease by 92.6%, 80.8%, 51.4% and 30.3% respectively, while the time distributions decrease by 48.4%, 27.5%, 10.7% and 4.8% respectively. These results are consistent with [230]. For $\eta = 0.07$, the Pareto distribution is similar to the results generated by our proposed p-NSGA-II. Compared to the p-NSGA-II solution sets with $\lambda_1 = 1$, $\lambda_2 = 0$ (most time robust), and $\lambda_1 = 0$, $\lambda_2 = 1$ (most energy robust) as shown in Figure 5.13, the sensitivity values of the RO solutions with $\eta = 0.07$ in Figure 5.16 (e) are distributed disorderly within the boundary constituted by the solutions optimized by p-NSGA-II, which implies that the η value can no longer play a role in selecting the robust solutions at this stage. When η is set to 0.01, there has been even no solution satisfying the sensitivity limit that can be found in the feasible region. Therefore, the solutions as the results of different η values are ambiguous and unpredictable. Sometimes, an inappropriate η value can lead to a narrowed solution distribution or even a null solution set. And the RO algorithm proposed in [230] cannot well manage different robustness indicators. Our proposed p-NSGA-II, on the one hand, can set the preferences of different robust indicators to generate the most-time-robust, most-energy-robust, or balanced solution

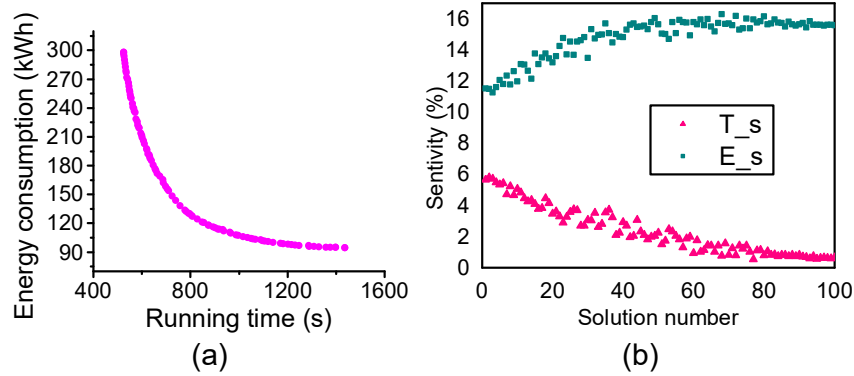


Figure 5.17: SO results. (a) SO Pareto front; (b) SO sensitivities.

sets. Furthermore, the solution distribution will not be narrowed while taking into account the requirements from dispatchers.

The SO was also applied. The passenger mass values are distributed as $M_p \sim N(80, 26^2)$ so that the range of the passenger mass is kept the same for different approaches. The Monte Carlo samples are set to 50 to calculate the perturbed objective vector. However, it was found that the perturbed objective vectors with η decreasing from 0.03 to 0.001 are very close to the objective vector calculated with the mean value of the train mass, which implies that the mean deviations of the energy consumption and running time are insensitive to the preset values. As shown in Figure 5.17 (a), the Pareto front is not further filtered compared with the original optimization with the mean value of the train mass even if the preset η value is sufficiently small ($\eta=0.001$). The solution sensitivities are also distributed disorderly as shown in Figure 5.17 (b). The perturbed objective vector by Monte Carlo samples shows the long-term patterns of energy consumption and running time for a specific driving strategy. It is evident that the solutions optimized by p-NSGA-II with the mean value of the train mass can sufficiently reflect the long-term operation situations and achieve long-term energy saving. While SO does not limit the maximum sensitivities (deviations) of energy consumption and running time. Furthermore, from Table 5.2, it can be found that the computational time of p-NSGA-II is longer than that of other algorithms except for SO method. This is expected because p-NSGA-II has the process of preference ranking, which leads to extra time-spending. While for SO, Monte Carlo sampling is needed hence resulting in far

more computational time than p-NSGA-II (nearly three times).

In summary, four algorithms, namely the conventional NSGA-II, RO algorithm, SO algorithm and the proposed p-NSGA-II are tested to verify the effectiveness and superiority of p-NSGA-II. The NSGA-II does not consider the robustness performance. Thus its solutions have the worse robustness in both energy consumption and journey time compared to the solutions obtained by p-NSGA-II under $\lambda_1 = 0.5$, $\lambda_2 = 0.5$. And the robustness of energy consumption is worse than that obtained by p-NSGA-II under $\lambda_1 = 0$, $\lambda_2 = 1$. The robustness of journey time is worse than that obtained by $\lambda_1 = 1$, $\lambda_2 = 0$. When RO algorithm proposed in [230] is applied, a pre-defined parameter η needs to be determined, which controls the convergent direction. As shown in Table 5.2, when η is set to have a small value such as $\eta = 0.02$, the distribution of the Pareto solutions is narrowed down significantly. If the dispatcher expects to choose the driving scheme with a short journey time below 965 s, the RO algorithm under $\eta = 0.02$ can not provide any satisfactory solutions. The same issue also happens when η is set 0.03, 0.05 and 0.06, and no suitable solutions can be provided to the dispatcher. When η is set a relatively large value such as $\eta = 0.07$, the distribution of the Pareto solutions is close to that obtained by p-NSGA-II. However, the average sensitivities of energy consumption and journey time obtained by RO algorithm under $\eta = 0.07$ are 14.3% and 1.9% which are worse than those of 13.9% and 1.8% obtained by p-NSGA-II under $\lambda_1 = 0.5$, $\lambda_2 = 0.5$ as shown in Table 5.2. And the average sensitivity of energy consumption is worse than that obtained by p-NSGA-II under $\lambda_1 = 0$, $\lambda_2 = 1$. The average sensitivity of journey time is worse than that obtained by $\lambda_1 = 1$, $\lambda_2 = 0$. Further, the RO algorithm can not control the energy consumption robustness and journey time robustness separately. It is evident from Table 5.2 that the RO algorithm shows these drawbacks when compared to the proposed p-NSGA-II. For the SO algorithm, first, it is more time-consuming than RO algorithm and p-NSGA-II due to the application of the Monte Carlo sampling method, and it also shows the worse robust performance for both energy consumption and journey time compared to the p-NSGA-II. For the proposed p-NSGA-II, not only can the energy consumption robustness and journey time robustness be controlled separately by adjusting weighting

factors, but also the distribution of the obtained Pareto front is always maintained. As shown in Table 5.2, under three different sets of weighting factors, the distribution of the solutions is comprehensive and close to that obtained by original NSGA-II without considering robustness. When the weighting factors are $\lambda_1 = 0$, $\lambda_2 = 1$, a set of solutions with lowest average sensitivity 13.7% of energy consumption is obtained compared to that obtained by other algorithms. When the weighting factors are $\lambda_1 = 1$, $\lambda_2 = 0$, a set of solutions with lowest average sensitivity 1.6% of journey time are obtained. It is consistent with the expectation for the weighting factors.

5.4.2 Case 2

In this case, the track considered is not on a flat surface but has ramps with different gradients as illustrated in Figure 5.18. It results in the whole journey being divided into 5 subsections with different speed limits based on the track gradients which are also revealed in Figure 5.18. Thus the corresponding control variable set is $V = (0, v_{1,c}, v_{1,b}, v_{1,e}, \dots, v_{5,s}, v_{5,c}, v_{5,b}, 0)$. There are 14 control variables in total to be determined considering $v_{i,e} = v_{i+1,s}$. In order to avoid the low average speed of the train resulting in a long journey time, the minimum cruising speed of the first four subsections is set to 30 m/s, and 15 m/s for the last subsection.

First, the optimization problem is solved by NSGA-II only considering scheme ro-

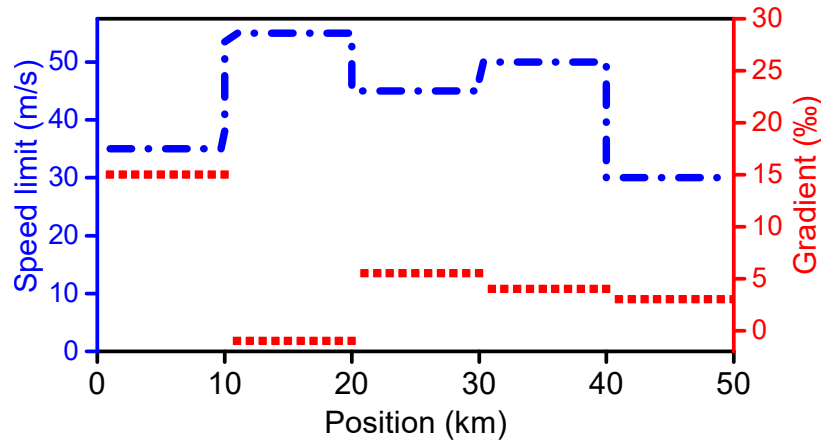


Figure 5.18: Track ramps in case 2.

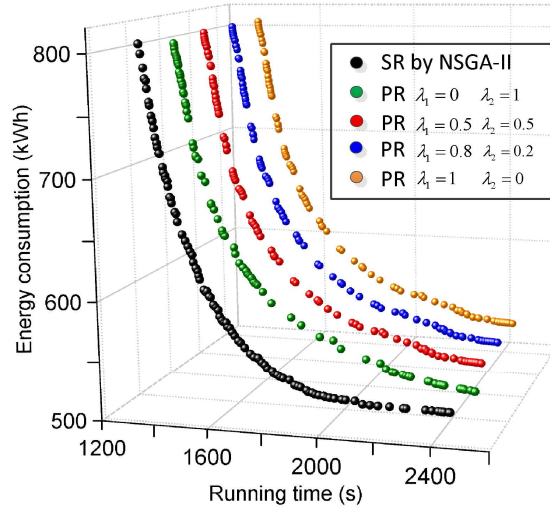


Figure 5.19: Comparisons of the Pareto fronts in case 2.

bustness but not performance robustness. The parameters for GA operations are still the same as those used in Case 1. Then the performance robustness is considered. Four cases with weighting factors ($\lambda_1 = 0, \lambda_2 = 1$) - most energy-robust, ($\lambda_1 = 0.5, \lambda_2 = 0.5$) - balanced, ($\lambda_1 = 0.8, \lambda_2 = 0.2$) - time robust priority, ($\lambda_1 = 1, \lambda_2 = 0$) - most time-robust, are performed. The Pareto fronts optimized by NSGA-II and proposed p-NSGA-II are shown in Figure 5.19. The spread of the Pareto fronts and corresponding computational time are listed in Table 5.2. The spread of the Pareto fronts optimized by p-NSGA-II is not getting significantly worse compared to that optimized by NSGA-II. Figure 5.20 shows the fastest and most energy-saving driving strategies obtained by p-NSGA-II which are labeled in red line and blue line respectively. The fastest driving strategy is obviously energy-consuming taking 809.6 kWh with a shortest journey time 1381 s. The most energy-saving driving scheme takes 523.1 kWh with a 2482 s journey time which has a 35.4% decrease of energy consumption compared to that of the fastest driving scheme. For the fastest driving strategy, the train always reaches the maximum allowable speed in each subsection and the coasting operation is rarely or never applied. For the most energy-saving driving strategy obtained, the full braking operation is rarely or never applied, instead the coasting operation is applied as much as possible. This is consistent with the conclusion drawn in [225].

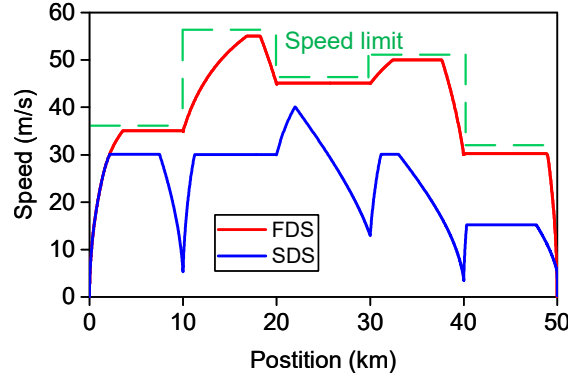


Figure 5.20: Fastest and most energy-saving driving schemes (FDS/ SDS).

Figs. 5.21-5.24 demonstrate the evolutionary convergence process of the p-NSGA-II under different weighting factors. As the iterations goes on, all solutions are guided to the Pareto front with lower sensitivities. This implies that a set of more robust driving schemes can be obtainable. The time sensitivities and energy sensitivities of the solutions optimized by the NSGA-II and p-NSGA-II are compared as shown in Figure 5.25 (a) and (b) respectively. In Figure 5.25 (a), the set of solutions under $\lambda_1 = 1$ and $\lambda_2 = 0$ have the overall lowest time sensitivities compared to the solution set under other weighting factors. With λ_1 increasing from 0 to 0.5, 0.8 and 1, the overall time sensitivity of the solutions overall decreases which implies that the time robustness of the solutions becomes better. As shown in Table 5.2, the average time sensitivity under $\lambda_1 = 1$ and $\lambda_2 = 0$ is 1.7% which is lower than that of 1.8% under $\lambda_1 = 0.5$, $\lambda_2 = 0.5$, 1.9% under $\lambda_1 = 0.8$, $\lambda_2 = 0.2$ and 2.0% under $\lambda_1 = 1$, $\lambda_2 = 0$. As shown in Figure 5.25 (b), the energy sensitivities of the solutions by p-NSGA-II under $\lambda_1 = 0$ and $\lambda_2 = 1$ are overall lower than

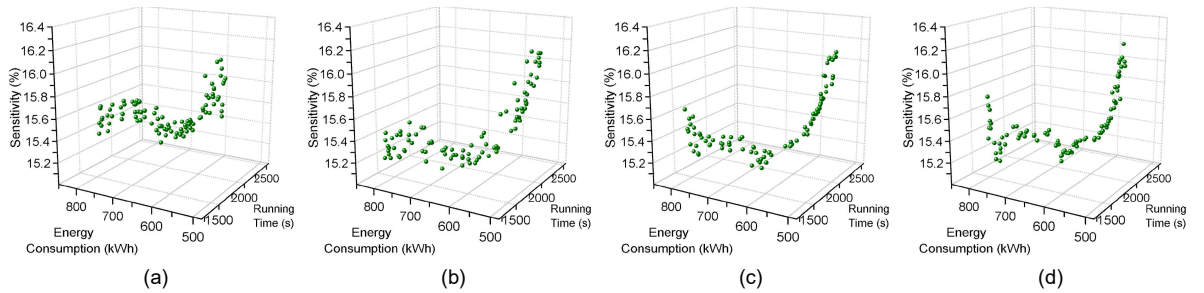


Figure 5.21: Iterations of p-NSGA-II under $\lambda_1 = 0$, $\lambda_2 = 1$. in case 2 (a) 20 iterations; (b) 50 iterations; (c) 75 iterations; (d) 100 iterations.

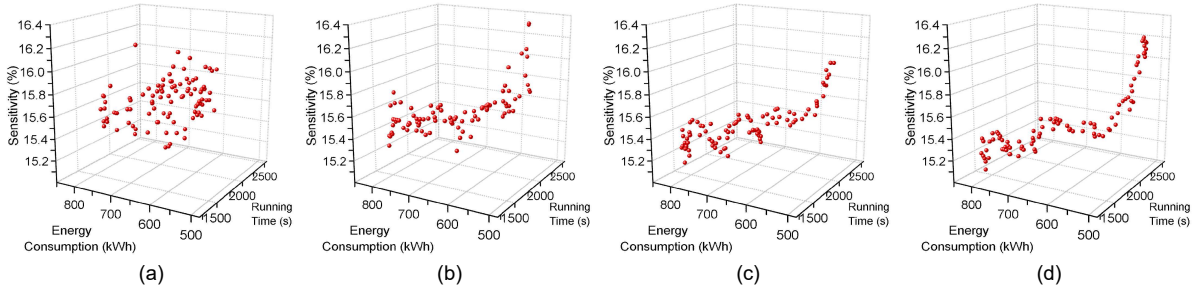


Figure 5.22: Iterations of p-NSGA-II under $\lambda_1 = 0.5$, $\lambda_2 = 0.5$. in case 2 (a) 20 iterations; (b) 50 iterations; (c) 75 iterations; (d) 100 iterations.

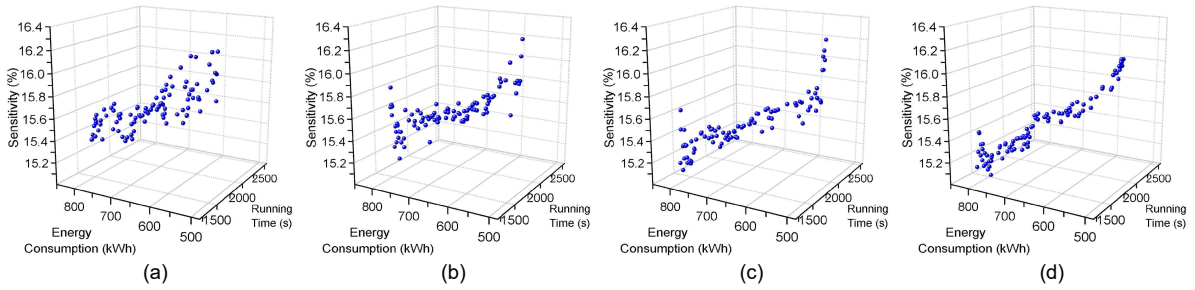


Figure 5.23: Iterations of p-NSGA-II under $\lambda_1 = 0.8$, $\lambda_2 = 0.2$. in case 2 (a) 20 iterations; (b) 50 iterations; (c) 75 iterations; (d) 100 iterations.

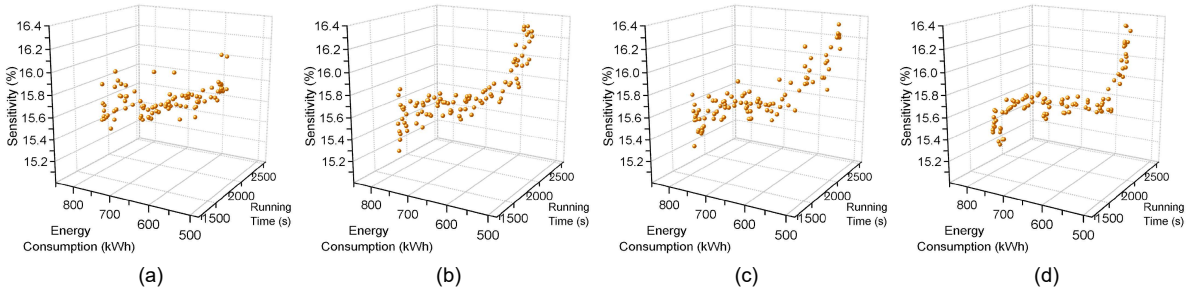


Figure 5.24: Iterations of p-NSGA-II under $\lambda_1 = 1$, $\lambda_2 = 0$. in Case 2 (a) 20 iterations; (b) 50 iterations; (c) 75 iterations; (d) 100 iterations.

those of solutions under other weighting factors. With λ_2 increasing from 0 to 0.2, 0.5 and 1, the overall energy sensitivity of the solutions decreases which implies that the energy robustness of the solutions becomes better. As shown in Table 5.2, the average energy sensitivity under $\lambda_1 = 0$ and $\lambda_2 = 1$ is 15.4% which is lower than that of 15.5% under $\lambda_1 = 0.5$, $\lambda_2 = 0.5$, 15.6% under $\lambda_1 = 0.8$, $\lambda_2 = 0.2$ and 15.8% under $\lambda_1 = 1$, $\lambda_2 = 0$. It is therefore confirmed that the proposed p-NSGA-II has shown to be capable of producing a set of robust Pareto solutions by adjusting the weighting factors based on the DM

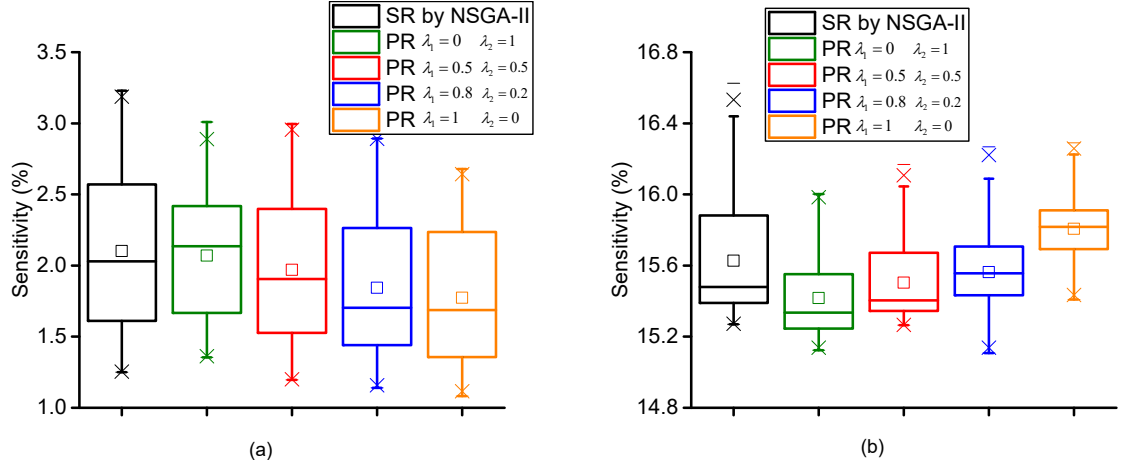


Figure 5.25: Comparisons of the Pareto fronts and solutions distribution under different situations in case 2. (a) Time sensitivity; (b) Energy sensitivity.

preference. The weighting factors of λ_1 and λ_2 dictate the journey time robustness and energy consumption robustness respectively. While in Figs. 5.25 (a) and (b), the time sensitivity and energy sensitivity of the solutions by NSGA-II are both relatively larger and distributed disorderly with an average time sensitivity 2.1% and an average energy sensitivity 15.6%. The average time sensitivity of the solutions obtained by NSGA-II is 23.5% higher than that of the solutions under $\lambda_1 = 1, \lambda_2 = 0$ obtained by p-NSGA-II. And the average time sensitivity of the solutions obtained by NSGA-II is 1.3% higher than that of the solutions under $\lambda_1 = 0, \lambda_2 = 1$ obtained by p-NSGA-II. Even if compared to the solutions under $\lambda_1 = 0.5, \lambda_2 = 0.5$, the solutions obtained by the original NSGA-II have lower overall and average robustness of journey time and energy consumption. These again confirm the effectiveness of the proposed p-NSGA-II.

5.5 Conclusion

This chapter has proposed a new DM preference based multi-objective optimization algorithm namely p-NSGA-II for robust train speed trajectories under the uncertainty of passenger load. This has been formulated as a bi-objective problem of minimizing energy consumption and running time, with specific constraints. By adding the scheme robustness constraint, the non-scheme-robust solutions are filtered out and all solutions

Table 5.2: Comparisons of different algorithms

		Energy distribution (kWh)	Running time distribution (s)	Computational time (s)	Average energy sensitivity (%)	Average time sensitivity (%)
Case 1						
NSGA-II (non-robust)		94.5-301.0	524-1436	152.58	14.3	1.8
NSGA-II (SR)		94.5-301.0	524-1436	489.51	14.2	2.0
p-NSGA-II	$\lambda_1 = 0 \ \lambda_2 = 1$	94.5-296.6	525-1436	993.21	13.7	2.5
	$\lambda_1 = 0.5 \ \lambda_2 = 0.5$	94.5-301.0	524-1436	985.60	13.9	1.8
	$\lambda_1 = 1 \ \lambda_2 = 0$	94.5-296.6	525-1436	953.35	14.4	1.6
RO	$\eta = 0.02$	94.5-109.7	965-1436	513.29	15.7	0.8
	$\eta = 0.03$	94.5-134.2	775-1436	498.64	15.6	1.1
	$\eta = 0.05$	94.5-194.8	622-1436	501.54	15.3	1.4
	$\eta = 0.06$	94.5-238.4	568-1436	536.86	15.1	1.6
	$\eta = 0.07$	94.5-296.8	525-1436	525.48	14.3	1.9
SO	$\eta = 0.001$	94.5-297.7	525-1436	2790.30	14.4	1.8
Case 2						
NSGA-II (SR)		525.4-807.7	1379-2461	958.52	15.6	2.1
p-NSGA-II	$\lambda_1 = 0 \ \lambda_2 = 1$	523.1-802.5	1384-2468	2618.65	15.4	2.0
	$\lambda_1 = 0.5 \ \lambda_2 = 0.5$	527.7-809.6	1381-2453	2526.68	15.5	1.9
	$\lambda_1 = 0.8 \ \lambda_2 = 0.2$	527.2-809.6	1381-2455	2568.56	15.6	1.8
	$\lambda_1 = 1 \ \lambda_2 = 0$	527.1-771.6	1395-2457	2683.52	15.8	1.7

are guaranteed to be feasible. The p-NSGA-II method has been developed to further search the performance-robust solutions within the feasible solutions. Two case studies have been conducted to verify the effectiveness of the proposed robust optimization approach. It is revealed that, compared to the optimization results obtained without considering performance robustness, the proposed approach p-NSGA-II can effectively produce a well spread-out and robust set of driving schemes with up to 40.59% average robustness improvement. Note that the proposed p-NSGA-II proves to be adept for the preference function-based multi-objective optimization problems, and thus can be easily applied to a number of other related engineering optimization problems.

CONCLUSION AND FUTURE WORK

This thesis has focused on the modelling, control and energy optimization for railway traction power supply system, taking into consideration of both the power supply and train operation aspects. Through this research, some significant challenges faced by the railway power sector in meeting the net zero target while maintaining the overall efficiency can be addressed. The findings have demonstrated the potentials of the proposed methods to improve the energy efficiency and drive the decarbonization of the railway sector, which is critical for achieving the UK as well as global climate goals.

6.1 Concluding Summary

The railway sector will continue to work towards the target of net zero by 2050. The discussions in this thesis align with the road map of the railway decarbonization covering both railway power supply side as well as the train operation side. The modelling of the co-phase system with renewable and ESS integration is performed. The optimization algorithms including the multi-objective algorithms and reinforcement learning algorithms are investigated. This thesis has presented a comprehensive discussions in the

following aspects:

In Chapter 2, a comprehensive review of the railway traction power supply systems and energy optimization techniques are performed. It begins with an overview of the traditional transformer-based power supply systems, power electronic power supply systems as well as smart railway power supply networks, discussing their configurations and characteristics. The chapter then proceeds to outline train traction systems, including current propulsion systems and the utilization of advanced technologies like on-board energy storage systems (ESS). Lastly, the chapter covers the review of energy optimization in railway traction power supply systems.

In Chapter 3, focusing on the railway power supply side, the co-phase system with renewable energy integration has been investigated and modelled. A bi-objective optimization problem is formulated considering both the power quality requirements of the three-phase power grid as well as the operation capacity of PFC. An optimization strategy based on NSGA-II algorithm has been proposed to reduce the system operation capacity while addressing the power quality issues for the co-phase system with renewable energy integration. A hybrid optimal compensation control scheme has also been developed to eliminate the negative sequence current caused by real-time prediction error. The simulation results confirm the validity of the proposed optimal compensation scheme, achieving an average of more than 20% reduction of operating capacity for the PFC compared to the full compensation scheme. Meanwhile, the power quality requirement is always satisfied, even in the presence of real-time prediction errors.

In Chapter 4, continuing to focus on the railway co-phase power supply system, the integration of ESS is considered. Besides meeting the requirements of the power quality, to enhance the reliability of the whole system, it is vital to limit the temperature increase for the key components including the power electronic devices and battery cells. Thus the thermal models of these devices are built in this chapter. A DQN-based energy management strategy is adopted to learn an optimized policy for power quality improvement, peak power shaving with the help of ESS while meeting the temperature constraints. Meanwhile, an FRA-based pruning method is then proposed to make the

agent more compact without compromising performance. Case studies confirm that the proposed strategy can effectively reduce the peak traction power supply by up to 42.0%, and achieve up to 94.1% temperature reduction. The FRA-based pruning can achieve up to 89.9% agent size reduction and 87.2% computation savings.

Chapter 5 focuses on the train operation, discussing the optimization for the train speed trajectories. A bi-objective robust optimization model to minimize both the energy consumption and journey time, in which the robustness against the uncertain train mass is considered and viewed as a decision-maker preference. To handle the DM preference, a novel multi-objective optimization algorithm namely p-NSGA-II is proposed, incorporating the original NSGA-II and a proposed preference dominance criterion.

Overall, this thesis covers various aspects of the railway traction power systems taking into considerations of the integration of renewable energy and ESS, optimization of train speed trajectories, etc. The research outcomes provide valuable theoretical foundations for enhancing energy efficiency, improving stability, and promoting decarbonization across the railway industry.

6.2 Suggestion for Future Work

This thesis has presented a comprehensive study on modeling, control, and energy optimization for railway traction power supply systems. However, despite the significant contributions made by this research, there remain several challenges that require further investigation. To advance the understanding of this topic, the following research areas are worthy of further study in the future.

Firstly, Chapter 3 concentrates on the cophase railway power supply system with renewable integration which takes into account the power quality issues and operation capacity of PFC. However, the adopted multi-objective optimization method NSGA-II is usually time consuming, so the optimization can be only performed offline. Thus it is necessary to investigate the methods to achieve the online optimization. Furthermore, as mentioned in this thesis, the uncertainty of the renewable energy will worsen the opti-

mization performance. The investigations of more accurate prediction for the renewable energy and stochastic optimization methods are meaningful for this system.

Secondly, in Chapter 4, the thermal models of the power electronic devices and battery cells are built. However, the achievement of the energy management strategy is based on the assumptions that the generated heat is distributed uniformly. That may not be the case in practice. The more accurate models are necessary to build in the future.

Furthermore, it is to be noted that the co-phase system can not fully solve the neutral section issues. In this context, the fully power-electronic-based power supply solution has become attractive. And it potentially bridges the gaps between the traditional railway power supply system and the smart railway power supply network. In the foreseeable future, fully power electronics based power supply substations with renewable and ESS integration, wayside DERs, and regional MGs could all be aggregated into the railway power supply network and provide flexible power flow as well as various grid services. It requires more investigations for configuring the network structure and controlling the power quality and energy flow.

Finally, from the train operation aspect, Chapter 5 investigates the optimization for the train trajectory considering the passenger load uncertainty. Another important research topic in the train operation side is timetable scheduling, and it can be more efficient in taking advantage of braking regenerative energy to concurrently optimize both train trajectory and timetable. Besides, on-board ESS offers the possibility to utilise the regenerative energy inside the train instead of transferring it to the overhead and dissipating part of it. The integration of on-board ESS is another potential research aspect.



INSTANTANEOUS POWER THEORY

The derivation of Equation 3.20 is detailed based on the traditional three-phase instantaneous pq theory. Firstly, it is assumed that the single-phase system is extended into a three-phase system with 120° phase difference between one another. The three-phase system is regarded as a virtual system with the voltage and current as follows:

$$\begin{cases} V_{acA} = V_{ac} \sin(\omega t) \\ V_{acB} = V_{ac} \sin(\omega t - 120^\circ) \\ V_{acC} = V_{ac} \sin(\omega t + 120^\circ) \end{cases} \quad (\text{A.1})$$

$$\begin{cases} I_{LA} = I_L \sin(\omega t - \varphi_L) \\ I_{LB} = I_L \sin(\omega t - \varphi_L - 120^\circ) \\ I_{LC} = I_L \sin(\omega t - \varphi_L + 120^\circ) \end{cases} \quad (\text{A.2})$$

In the instantaneous pq theory, the Clarke transform is adopted and the three-phase coordinate system is transformed into an orthogonal system as follows:

$$\begin{bmatrix} V_{ac0} \\ V_{ac\alpha} \\ V_{ac\beta} \end{bmatrix} = \sqrt{\frac{2}{3}} \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} \begin{bmatrix} V_{acA} \\ V_{acB} \\ V_{acC} \end{bmatrix} = \begin{bmatrix} 0 \\ \sqrt{3} V_{ac} \sin(\omega t) \\ \sqrt{3} V_{ac} \cos(\omega t) \end{bmatrix} \quad (\text{A.3})$$

$$\begin{bmatrix} I_{L0} \\ I_{L\alpha} \\ I_{L\beta} \end{bmatrix} = \sqrt{\frac{2}{3}} \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} \begin{bmatrix} I_{LA} \\ I_{LB} \\ I_{LC} \end{bmatrix} = \begin{bmatrix} 0 \\ \sqrt{3}I_L \sin(\omega t - \varphi_L) \\ \sqrt{3}I_L \cos(\omega t - \varphi_L) \end{bmatrix} \quad (\text{A.4})$$

Then the virtual three-phase instantaneous power can be calculated as

$$S_{L_{3p}} = \tilde{V}_{ac} \cdot \tilde{I}_L^* = (V_{ac\alpha} + jV_{ac\beta}) \cdot (I_{L\alpha} - jI_{L\beta}) \quad (\text{A.5})$$

The instantaneous active and reactive power of the virtual three-phase can be expressed as

$$\begin{bmatrix} p_{L_{3p}} \\ q_{L_{3p}} \end{bmatrix} = 3 \begin{bmatrix} V_{ac} & V_{ac}e^{-j\frac{\pi}{2}} \\ V_{ac}e^{-j\frac{\pi}{2}} & -V_{ac} \end{bmatrix} \begin{bmatrix} I_L \\ I_L e^{-j\frac{\pi}{2}} \end{bmatrix} \quad (\text{A.6})$$

Thus the instantaneous active and reactive power of the original single phase system is

$$\begin{bmatrix} p_L \\ q_L \end{bmatrix} = \begin{bmatrix} V_{ac} & V_{ac}e^{-j\frac{\pi}{2}} \\ V_{ac}e^{-j\frac{\pi}{2}} & -V_{ac} \end{bmatrix} \begin{bmatrix} I_L \\ I_L e^{-j\frac{\pi}{2}} \end{bmatrix} \quad (\text{A.7})$$

PUBLICATIONS

Journal Papers

1. C. Xing, K. Li, and J. Su, "Thermal constrained energy optimization of railway co-phase systems with ess integration - an fra-pruned dqn approach," *IEEE Transactions on Transportation Electrification*, Accepted on 2022. DOI: 10. 1109/ TTE. 2022. 3218762
2. C. Xing, K. Li, L. Zhang, and Z. Tian, "Robust optimization of energy-saving train trajectories under passenger load uncertainty based on p-nsga-ii," *IEEE Transactions on Transportation Electrification*, vol. 9, no. 1, pp. 1826–1844, 2022
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4. J. Su, K. Li, Y. Li, C. Xing, and J. Yu, "A novel state-of-charge-based droop control for battery energy storage systems to support coordinated operation of dc microgrids," *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 11, no. 1, pp. 312–324, 2023
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